Quantifying and Visualizing Risk in the Garment Manufacturing Supply Chain

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ABSTRACT

Supply chains are exposed to a variety of risks as they become more complex and geographically diverse. Disruptions due to these risks can be costly. Companies cannot hope to mitigate all of their supply chain risks. In order to focus risk management resources on locations in the supply chain with the most risk, companies need a comprehensive method to quantify all of their significant supply chain risks. We worked with a company in the garment manufacturing industry to map their supply chain for a few representative products. Using input from the company, we equated different risk indices with the probability of loss of a node in their supply chain. The probabilities of loss allowed us to calculate a value-at-risk at each node. Once calculated, the values-at-risk were overlaid on a visual depiction of the company's supply chain network. While previous studies have quantified and visualized risk in companies' supply chains, our research sought to combine different categories of risk in order to give a more comprehensive picture of the risk at each node. We looked at disruption risks due to natural disasters, supplier bankruptcy, and political instability. We found that commercially available indices that quantify different categories of risk can be used to inform supply chain risk management decisions. Moving from these indices to a value-at-risk model of a supply chain is not a wholly quantitative process. Therefore, the strength of the model lies more in the relative quantities of value-at-risk rather than their absolute values. Overlaying these values-at-risk over a visual depiction of their supply chain gave the company a clearer picture of where to focus risk management efforts. Other companies in other industries could apply a similar approach to build an organizational risk management tool.

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1. INTRODUCTION

In pursuing low-cost manufacturing, many companies have moved production farther away from their customers. This is especially the case in industries with labor-intensive manufacturing. Suppliers for these industries are also generally located in low-cost areas. When manufacturing is outsourced to low-cost areas, a number of factors combine to increase companies' supply chain risk. In addition to the increased lead time to transport finished goods to market, the low-cost countries generally have less robust infrastructure to protect against and recover from natural disasters. They are also exposed to increased geopolitical risks from regional conflicts, criminal violence, and corruption. When manufacturing and sourcing in low-cost areas, the lower direct manufacturing costs need to be balanced with the often indirect costs from increased supply chain risk.

Companies must be able to quantify and visualize the risk in their supply chain in order to effectively manage it. Efforts have been made in the past to quantify the value-at-risk in supply chains due to the effects of natural disasters. We built a model which considers additional factors that pose risks to companies' supply chains. By combining the risks from natural disasters, suppliers' financial instability, and geopolitical events, we plan to gain insight on the value-at-risk at nodes in a company's supply chain. When companies are presented with a clear map of their supply chain overlaid with relative values-at-risk at each node, their risk management decision-making is simplified.

In our thesis, we explain the data collection process required for mapping a company's supply chain and calculating the value-at-risk at each node. We discuss the different sources of risk we used to calculate loss probabilities for each supply chain node and how values-at-risk were then determined for the same nodes. We also show the results of visualizing the value-at-risk in the company's supply chain using SourceMap. With the results, we take a closer look at a couple of nodes with relatively high value-at-risk and discuss potential ways to lower the risk. Any company should be able to replicate our work in order to build a model for effective supply chain risk management.

2. LITERATURE REVIEW

With the continuous increase in global business interaction, supply chain management tends to eliminate excess inventory and adapt a just-in-time supply chain strategy. However, there is a trade-off between eliminating excess inventory and the cost of disruptive risks. To make effective and efficient inventory decisions, it is important to know not only the cost of inventory, but also the value-at-risk when a disruption event occurs in a global supply chain transaction. Traditionally, quality auditors mainly focused on internal risk control to meet the requirements of corporate social compliance, including environmental sustainability, community responsibility, and ethical working conditions. But according to Paul Myerson (2012), the supply chain is at risk of disruptions caused by multiple sources, such as geopolitical, financial, environmental, and other unplanned events, and these disruptions are occurring at a seemingly ever-increasing rate. More and more corporations started to pay attention to the risks from specific disruptive events, such as natural disaster. Stecke and Kumar (2009) sought to confirm statistically the increase in quantity and severity of supply chain disruptions by analyzing data from a wide variety of sources. Figure 1 shows the average natural catastrophes reported and yearly economic losses caused over the past century. The economic losses may be impacted by both the natural catastrophes event itself and the impact of the news spreading in the industry. Data from geopolitical risk experts at Aon also show increasing level of supply chain disruption due to geopolitical risk (Aon 2016). However, there is no study focused on measuring the value-at-risk from the combination of conventional and unconventional risks such as the risk of natural disasters, geopolitical events, and suppliers' financial instability.

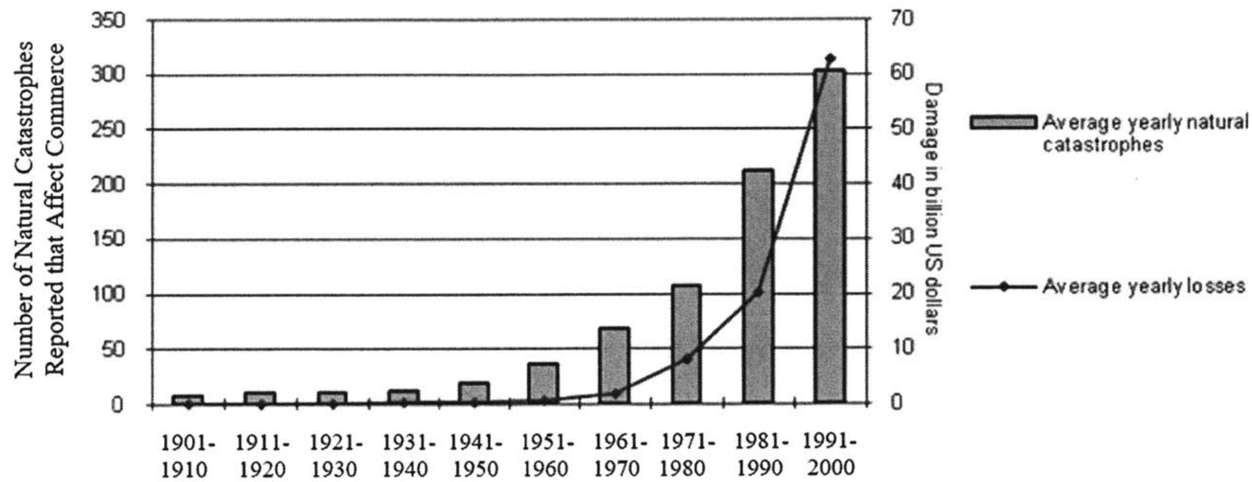

Figure 1. Natural Catastrophes Reported and Yearly Economic Losses Caused (Stecke and Kumar 2009, p. 201).

It is critical to know the potential cost of disruptive risks to make strategic decisions in a global supply chain. Our thesis seeks to improve upon the modeling of varied categories of disruption risks. By converting financial impact of supply chain disruption to a risk exposure index, we can use a value-at-risk model to quantify the risk at different nodes in a supply chain. When value at risk is visualized as a network using supply chain mapping software, the effect of disruptions at one node across the entire supply chain can be linked, quantified and visualized. We conducted a review of literature on combining different risk categories in order to visualize vulnerabilities in a supply chain. First, we give a brief overview of the complexity of supply chains in the industry we studied, the garment manufacturing industry. Following the overview are sections reviewing the identification, evaluation, modeling, and mapping of risks in supply chains. Finally, we cover some of the current prevailing methods for mitigating the vulnerabilities once they are identified and visualized.

2.1 Garment Manufacturing Industry

The garment manufacturing process involves two main steps, cutting and sewing, which are both labor intensive. The main raw materials sourced to the sewing plants for garment production are fabric, thread, buttons, lining, zippers, and labels. The garment manufacturing industry has not kept pace with productivity-increasing automation technologies as other manufacturing industries have (Nayak & Padhye 2015). Due to the availability of cheaper labor in certain areas of the world, many companies have relocated their cutting and sewing plants or outsourced these activities to the lower-cost areas. Often, the markets served by the garments manufactured in these areas are not in the same geographic region as the manufacturing plants (Kilduff 2005). Close coordination of the supply chain becomes imperative in this situation, and the brand owners typically take the lead in coordinating it (Cao et al 2008). Figure 2 highlights some of the complexities in the industry's supply chain. Sourcing decisions made to lower production costs in the garment manufacturing industry often introduce additional risks into their supply chains.

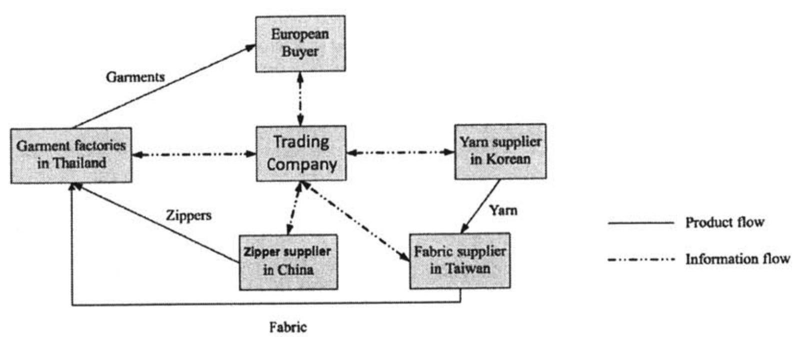

Figure 2. Conceptual Flow of Materials in Garment Manufacturing Supply Chain derived from (Cao 2008, p. 393).

2.2 Risk Identification

Studies of supply chain risks focus on the risk of disruption to a supply chain. A disruption could occur at a supplier, a manufacturing plant, a distribution center, a retailer, or during transit between any two of these points. As shown in Figure 3, Zsidisin (2008) attempts to categorize all factors that can lead to a disruption in the supply chain. While some supply chain disruption risks are apparent, it is not the case with all of the risks.

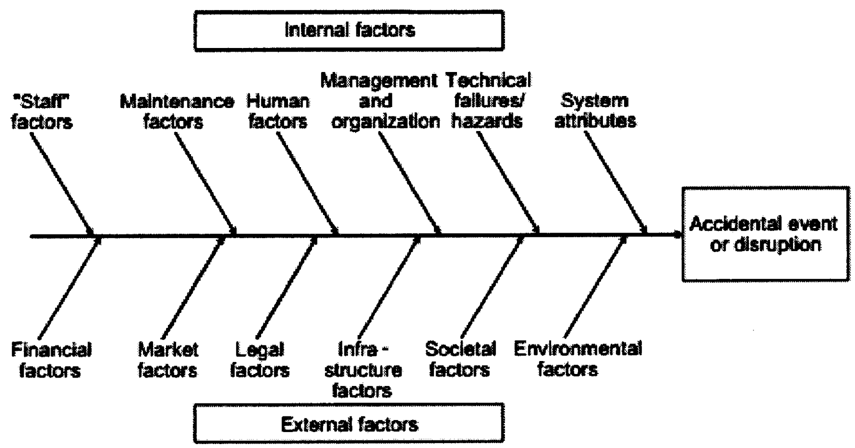

Figure 3. Internal and External Risk Factors to the Supply Chain (Zsidisin 2008, p. 27).

While our thesis does look at some commonly identified supply chain risks, we also explore less apparent risks to a supply chain. The risk of disruptions due to geopolitical events are not as apparent as the risk of disruptions due to natural disasters or suppliers' financial instability. What we refer to as geopolitical risks, Manners-Bell (2014) refers to as societal risks. Certain events that are more geopolitical in nature than environmental fall into this category such as international terrorism, criminal violence, regional conflict, etc.

2.3 Risk Impact

Much research has been done to evaluate disruptive risks in different areas, and how these risks may have unpredictable and disruptive impact on a global supply chain. It is critical for global supply chain operation to proactively and strategically manage the potential risks from natural disasters, geopolitical events, and financial instability. The 2010 Icelandic volcano eruption caused the three largest airports in Europe to stop operations for seven days; many companies were affected by the air cargo disruption, and had to stop production due to a corresponding shortage in supply (Icelandic Volcano Eruption 2010). Moreover, the 9/11 terrorism attack shut down several manufacturing plants and caused serious drops in their productions, partially because of the material shortage. In addition, the financial bankruptcy risk is a major concern for many global supply chain partnerships. In 2001, Land Rover's solo supplier of chassis, UPF Thompson, declared bankruptcy and took advantage of being a sole partner with Land Rover by demanding sixty-five million dollars in exchange for resuming chassis shipments (Babich 2010). Sheffi emphasized that "the threat of terrorism and other risks, is affecting not only the 'physical' supply chain, but also the organizational dimension of company, to the point of affecting the whole corporate strategy" (Sheffi 2003). The research conducted by Xia and Liu (2014) has individually measured the natural disaster risk impact and value-at-risk. However, very little research has been done on combining the risks from natural disasters, geopolitical events, and supplier's financial stabilities. Next, we look at existing methods in which these three varied categories of disruption risks could be combined to reasonably estimate the level of risk at different geographic locations within the global supply chain.

2.4 Risk Models

Many measurement models have been developed for risk modeling, but these models are created for specific areas of risks. For example, AIR Worldwide is one of the leading teams in researching natural catastrophes. AIR Worldwide provides catastrophe modeling data to various industries, such as insurance companies, financial institutions, and governments, based on the geographic locations. By locating the transaction nodes within the supply chain, AIR Worldwide simulates the probability of impact from various natural disasters for the given locations.

In geopolitical risk measurement, Verisk Maplecroft is another organization specializing in analyzing real-time geopolitical risks. Verisk Maplecroft provides different categories of risk indices for 198 countries to helps multinational organizations to strengthen the risk management processes. The risk categories include four major areas, including geopolitical risks, economic risks, human right, and environmental risk.

The study of financial bankruptcy prediction started in mid-1960's, focused on comparing and distinguishing the financial characteristics between companies who filed and not file the bankruptcy. William Beaver (1966) studied 29 financial ratios to identify and differentiate the ratios from the 79 sampled bankrupt companies and 79 non-bankrupt companies. The analysis helps identify the factors related to bankruptcy, such as long term solvency risk and liquidity risk, but the analysis does not provide any further correlative measurement between the risk level and financial ratio. Later, Altman (1968) used the sampled manufacturers' data to develop the prediction model, by controlling and testing varied ratios, then applying the model to separate samples to check the predictability. The model, shown in Figure 4, analyze financial statements by calculating a score based on a firm's past performance in order to predict its future economic condition. The Z-Score indicates the probability of a company entering bankruptcy within the next two years, and the higher the value, the lower the probability of bankruptcy. By examining the pattern of Type I and Type II errors, Altman chose the cutoff points that distinguish three levels of bankruptcy risk.

$$
\begin{aligned}
&\text{(I)} \quad Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5 \\
&\text{where } X_1 = \text{Working capital/Total assets} \\
&\qquad X_2 = \text{Retained Earnings/Total assets} \\
&\qquad X_3 = \text{Earnings before interest and taxes/Total assets} \\
&\qquad X_4 = \text{Market value equity/Book value of total debt} \\
&\qquad X_5 = \text{Sales/Total assets} \\
&\qquad Z = \text{Overall Index}
\end{aligned}
$$

Figure 4. Altman's Bankruptcy Prediction Model (Altman 1968, p. 594).

If the supply chain operation has very high risk exposure to all risk factors, the supply chain is more vulnerable and it is more difficult to recover during disruptive events. Therefore, finding the value-at-risk for the combination of the conventional and unconventional risks is necessary.

One of the most commonly used matrices to monitor supply chain risks is the Risk Rating Matrix (Fike 2005). The risk categories are listed and auditors rank the different levels of risks on color scale. However, it is challenging to achieve rating consistency among various auditors and categories. Another commonly used model is the Weighting and Scoring System for Risk Matrices, but the outputs will be influenced by comparative relationship among variable risks (Beasley et al 2006). We found it would be more accurate to consult with professional risk prediction experts to determine the probabilities of natural disaster risks and geopolitical events, and determine the financial instability based on a company's public financial statements.

Another risk analysis method developed by Aqlan and Lam (2015) is the Bow-Tie Analysis of Supply Chain Risks, which collects the probabilities of occurrence from the causes and transfers the probability into a dollar value as consequences (Figure 5).

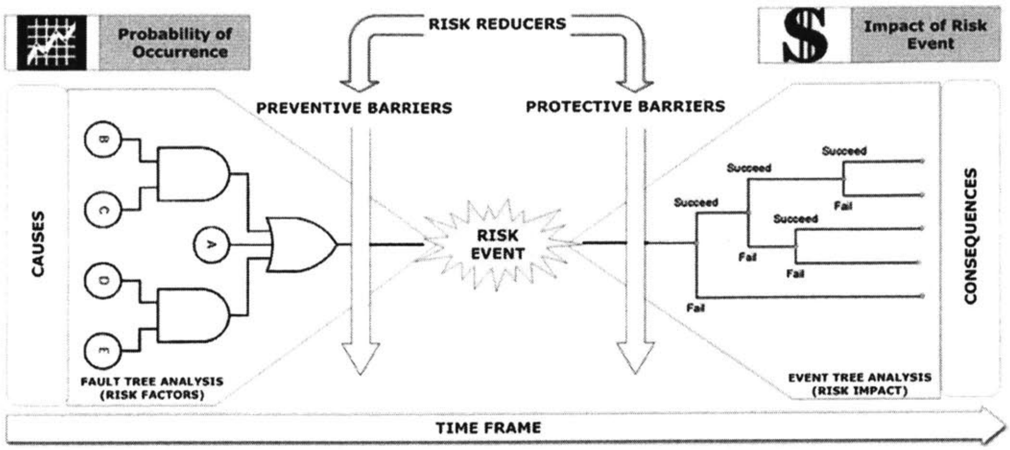

Figure 5. Supply Chain Modeling and Mitigation (Aqlan and Lam 2015, p. 56).

The existing models are more or less based on personal judgments, but risk modeling can have a huge impact in strategic decision-making. We want to create a model with a more quantitative and visual method to link and evaluate the values-at-risk for daily operation in a global supply chain network.

2.5 Risk Mapping

To better display the value-at-risk across the supply chain, mapping is a helpful tool to visualize global supply chain risks and their connections. John Tukey (1997) mentioned that the greatest value of a picture is when it forces us to notice what we never expected to see. Today's supply chains are not simply about the flow of physical goods. With the increasing development of ERP systems collecting large amounts of data, it is important to convert this data into actionable information. IBM (2013) emphasized that information and feature extraction is much easier when data is visualized, compared to working with raw numbers. Visualization helps to quickly identify risk exposure for a global supply chain. In our project, we will use SourceMap, a provider of web-based supply chain visualization solutions, to transform data into different risk visualizations.

2.6 Risk Mitigation

Unmitigated risks may lead to costly disruptions to a company's supply chain. As seen in Figure 6, there are a variety of mitigation techniques depending on which type of risks you are mitigating. A study by Fike (2005) suggests centralizing responsibility for supply chain risk mitigation within a company's internal audit department. The study offers a good framework for mitigating risks without any specific risk mitigation techniques. Other studies were more focused on mitigating risks based on quantifying the value of specific methods. Huang and Liu (2014) used the return on assets (ROA) metric to evaluate the effect of holding additional

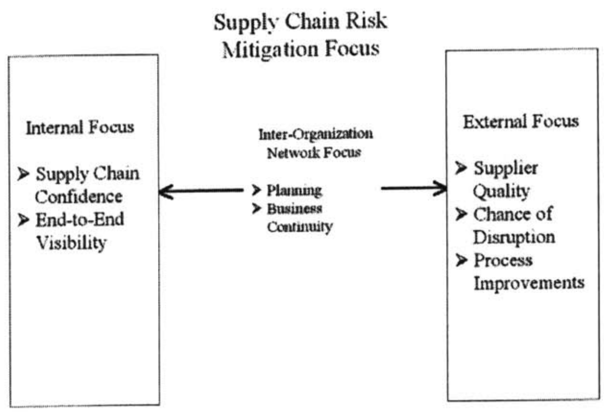

Figure 6. Common Focus Areas in the Mitigation of Supply Chain Risks (Fike 2005, p. 4).

inventory versus increasing supplier base. Xia and Liu (2014) took a similar approach to our research in identifying, quantifying, and visualizing a company's supply chain risks. They found that dual sourcing, increasing inventory levels, lowering reliance on upstream strategic partners, and storing safety stock at multiple locations were effective ways to mitigate risk. Our thesis will evaluate a broader range of risks than Xia and Liu (2014) in a similar manner. Another study showed that risk should be measured and mitigated not only at a single node but across an entire network (Buscher and Poyato Ayuso 2015). Our research will compare different scenarios to evaluate the effect of changes at one node across the entire supply chain.

2.7 Conclusion

Recently, much research has been done regarding the identification, modeling, visualization, and mitigation of risks inherent in complex, global supply chains. Our thesis seeks specifically to improve upon the modeling of varied categories of disruption risks. By converting risk indices into risk probabilities and other data into a risk exposure index, we can use a value-at-risk model to quantify the risk at different nodes in a supply chain. When this data is visualized as a network using supply chain mapping software, the effect of disruptions at one node across the entire supply chain can be quantified and visualized. Visualizing the disruption risk across the network will lead to more informed decisions when a company is seeking methods to mitigate these risks.

3. METHODOLOGY

Our thesis seeks to develop an approach to quantify and visualize the combination of conventional and unconventional risks in our sponsor company's supply chain in order to foster better risk management decisions. We first focus on displaying the interconnected structure of supply chain operating network. Second, we develop a model to combine the likelihood of different risk occurrence based on the different risks indices, including natural disaster risk, financial instability of suppliers, and geopolitical risk. Third, we quantify the risk exposure and value at risk for each supply location.

3.1. Scope Identification

As a garment manufacturer, our sponsor company manages a large number of stock keeping units (SKU). The variety of sizes, colors, and other customization options within their two most profitable product groups led to SKU proliferation. We decided to look at a couple of their product groups which accounted for the largest portion of the company's revenues. One of the product groups was a line of pants and the other was a line of shirts. Within the two product groups, there were over 6,000 different SKUs. From these 6,000 SKUs, we created two representative products that modeled the product groups. We were able to designate such a small number of representative products from the large number of SKUs in each product group for a number of reasons. Most importantly, the supply chains for the garments comprising the majority of the SKUs in each of the product groups are fairly similar. Secondly, shirts of different sizes or different colors have slightly different bills of materials (BOM); however, components that are only slightly different are still usually sourced from the same suppliers. By identifying the scope of the products whose supply chains we were mapping up-front, we were able to undertake a more surgical approach to gather the remaining data required for analysis.

Figure 7 outlines the data we collected from our sponsor company in order to map the products' supply chains and calculate the value-at-risk at the different nodes.

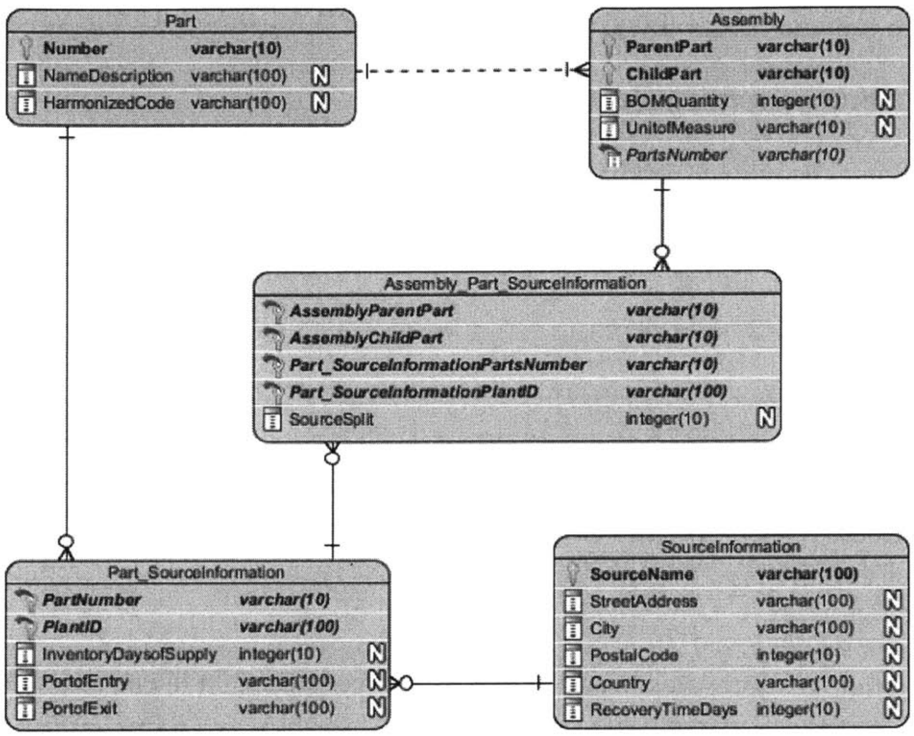

Figure 7. Upstream Data UML Entity Relationship Diagram.

3.2. Risk Identification

The majority of supply chains in the garment manufacturing industry are global. Their international operations expose them to a variety of risks. In our research, we came across hundreds of different risk categories. While we could not attempt to model the impact of all of these risks, our sponsor company helped us select the most significant sources of disruptive supply chain risk from their perspective: natural disasters, geopolitical events, and supplier financial instability. After selecting types of risk to focus on, we sought out indices which quantified those risks.

3.2.1. Geopolitical Event Indices

We received indices of geopolitical events from Verisk Maplecroft (Appendix A), a company which provides geopolitical risk services for various industries. Our sponsor company assisted us in selecting the five indices listed below:

1. International Regional Conflict Index
    - Assesses a country's exposure to regional conflict.
2. International Terrorism Index
    - Assesses a country's exposure to international terrorism.
3. Criminal Violence Index
    - Assesses the risk of homicide, kidnapping, robbery, and the business cost of crime.
4. Corruption Index
    - Examines the prevalence and persistence of corruption in the public and private sectors, as well as the efficacy of government efforts to combat corruption.
5. Political Risk Index
    - Assesses risks to business emanating from direct government action, or as a result of action by sub-state or other politically-motivated groups.

Each of the selected risk indices ranged between 0 and 10 with four grading bands.

- Extreme Risk: 0.00 to 2.50 points
- High Risk: 2.51 to 5.00 points
- Moderate Risk: 5.01 to 7.50 points
- Very Low Risk: 7.51 to 10.0 points

By identifying all of the nodes in the supply chain, we were able to use Verisk Maplecroft's geopolitical indices to determine geopolitical risk at the geographic locations of interest to our sponsor company.

3.2.2. Natural Disaster Indices

AIR Worldwide was the source of the natural disaster risk indices we used. They are a provider of various catastrophic risk indices and service solutions for different industries (Appendix C). Once provided with the geographic locations of our supply chain nodes, AIR Worldwide ran catastrophe model simulations for these locations. From these simulations, they provided us with a range of expected building damage values at each node based on the frequency of the disasters' occurrence.

3.2.3. Altman Z-Score

Past studies of the Altman Z-Score have shown that this metric can be used to provide a reasonable expectation as to whether or not a company will go bankrupt in the next one to five years (Altman 1968). Table 1 shows the zones of discrimination for three ranges of the Altman Z-Score. Calculating the metric requires access to a company's balance sheet and income statement. For companies with publicly available financial statements, we calculated the Altman Z-Score using the following values:

- Total Assets
- Total Liability
- Working Capital
- Retained Earnings
- Market Value of Equity
- Sales

Table 1. Altman Z-Score to Zone of Discrimination (Altman 1968).

Altman Z-Score	Zone of Discrimination
$Z>2.99$	Safe
$1.81<Z<2.99$	Grey
$Z<1.81$	Bankrupt

Our sponsor company's purchasing department was able to provide us with z-scores for some private suppliers. For other private companies without an accessible balance sheet or income statement, a financial probability of loss had to be estimated. OneSource Business Browser (Infogroup 2016). offers online access to business information for researching companies. To better estimate a private supplier's financial instability, we searched the following factors in the OneSource Business Browser:

- Risk Propensity (Low Risk/Moderate Risk/High Risk) – A measure of a company's financial risk based on payment history.
- Spending Rate (Growing/Stable/Declining) - Reflects the company's most recent 3-months of purchasing behavior.
- Size of the Company (Number of Employees)

We created a matrix to compare these factors with companies for which we were able to calculate an Altman Z-Score. As shown in Table 2, the matrix includes twenty-seven different combinations of the factors. We weighted each of the factors according and rank ordered the different combinations:

- Low Risk Propensity = 1, Moderate Risk Propensity = 3, High Risk Propensity = 5.
- Growing Spending Rate = 1, Stable Spending Rate = 2, Declining Spending Rate = 3.
- Large Size = 1, Medium Size = 2, Small Size = 3.

We weighted risk propensity more, assuming it would have a higher correlation with probability of bankruptcy. According to Table 1, a Z-Score above 2.99 is in the safe zone and a Z-Score below 1.81 is in the bankrupt zone. In Table 2, we assigned the minimum combined financial index of 3 to a probability of bankruptcy of 2.27% (Altman Z =3.0) and the maximum combined financial index of 11 to a probability of bankruptcy of 21.15% (Altman Z = 1.80). We assumed a linear relationship between the combined financial index and the probability of bankruptcy.

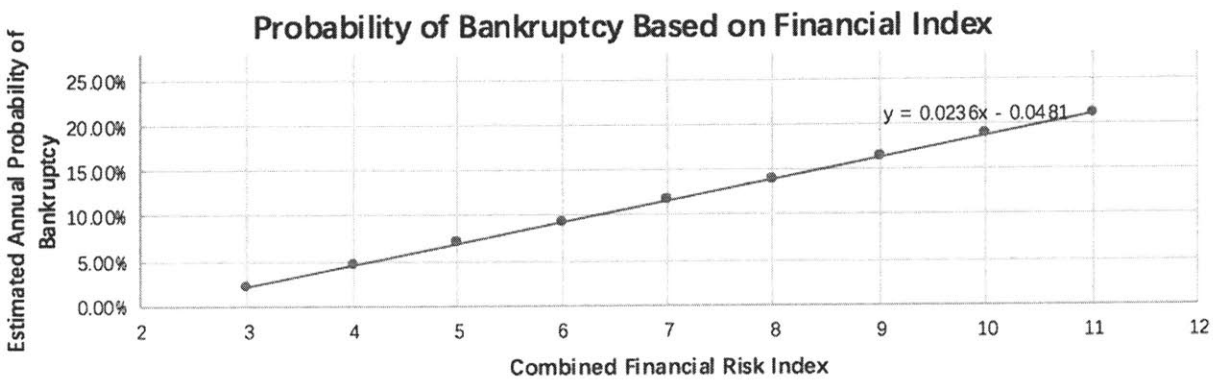

Figure 8. Estimate Probability of Bankruptcy.

This analysis allowed us to estimate probabilities of bankruptcy within the next year for the private companies for which we were unable to obtain an Altman Z-Score. For example, if the supplier was labelled as low risk in terms of risk propensity, with a growing spending rate, and a large company size, we estimated that the probability of bankruptcy within a year would be 2.27%. If the supplier was classified as high risk in terms of payment history, with a declining spending rate, and a small company size, we estimated the probability of bankruptcy for next year to be 21.15%.

While this method was less than ideal for calculating the probability of bankruptcy of our sponsor company's private suppliers, we used the information available to us to make an estimate. If time allowed, sensitivity analysis could have been conducted to find the correlation between the probability of bankruptcy and the factors we utilized. A more robust approach would be for our sponsor company to require suppliers to provide the information required to calculate the Altman Z-Score as a precursor to doing business.

Table 2. Information Used to Estimate Probabilities of Bankruptcy from OneSource Business Browser.

Risk Propensity	Risk Propensity Index	Spending Rate	Spending Rate Index	Company Size	Company Size Index	Sum of Index	Estimated Annual Probability of Bankruptcy
Low Risk	1	Increasing	1	Large >10,000	1	3	2.27%
Low Risk	1	Increasing	1	Medium 200-10,000	2	4	4.63%
Low Risk	1	Stable	2	Large >10,000	1	4	4.63%
Low Risk	1	Decreasing	3	Large >10,000	1	5	6.99%
Low Risk	1	Increasing	1	Small <200	3	5	6.99%
Moderate Risk	3	Increasing	1	Large >10,000	1	5	6.99%
Low Risk	1	Stable	2	Medium 200-10,000	2	5	6.99%
Low Risk	1	Decreasing	3	Medium 200-10,000	2	6	9.35%
Moderate Risk	3	Increasing	1	Medium 200-10,000	2	6	9.35%
Low Risk	1	Stable	2	Small <200	3	6	9.35%
Moderate Risk	3	Stable	2	Large >10,000	1	6	9.35%
Low Risk	1	Decreasing	3	Small <200	3	7	11.71%
Moderate Risk	3	Decreasing	3	Large >10,000	1	7	11.71%
High Risk	5	Increasing	1	Large >10,000	1	7	11.71%
Moderate Risk	3	Increasing	1	Small <200	3	7	11.71%
Moderate Risk	3	Stable	2	Medium 200-10,000	2	7	11.71%
Moderate Risk	3	Decreasing	3	Medium 200-10,000	2	8	14.07%
High Risk	5	Increasing	1	Medium 200-10,000	2	8	14.07%
High Risk	5	Stable	2	Large >10,000	1	8	14.07%
Moderate Risk	3	Stable	2	Small <200	3	8	14.07%
High Risk	5	Decreasing	3	Large >10,000	1	9	16.43%
Moderate Risk	3	Decreasing	3	Small <200	3	9	16.43%
High Risk	5	Increasing	1	Small <200	3	9	16.43%
High Risk	5	Stable	2	Medium 200-10,000	2	9	16.43%
High Risk	5	Decreasing	3	Medium 200-10,000	2	10	18.79%
High Risk	5	Stable	2	Small <200	3	10	18.79%
High Risk	5	Decreasing	3	Small <200	3	11	21.15%

3.3. Risk Quantification

We identified three categories of supply chain risk of interest to us and sources for the information. Our next step was to find a way to quantify the cumulative risk of the different categories of risk on our sponsor company's supply chain. We accomplished this through the use of the value-at-risk calculation. The value-at-risk calculation involves multiplying a risk exposure index by the probability of a disruption.

3.3.1. Value-at-Risk

Value-at-risk is the product of the risk exposure index and the probability of disruption at a node in the supply chain. The calculation gives insight into how much revenue could potentially be lost by losing a node in the supply chain as well as the likelihood the node in the supply chain will be lost. For our thesis, the value-at-risk was calculated at each node in our sponsor company's supply chain.

3.3.2. Risk Exposure Index

To determine the value-at-risk at each node in our sponsor company's supply chain, a risk exposure index was calculated for every location. The risk exposure index is a function of the inventory days of supply available for a specific component, the days to recovery following the loss of a supplier, and, most importantly, the revenue at risk from the loss of a supplier. Our sponsor company was able to provide us with their planning factors for inventory days of supply for components and finished goods. Since the actual inventory days of supply would change daily, their planning factors for how much stock of components and finished goods to maintain were seen as suitable alternatives. Our sponsor company also provided us with the days to recover following loss of a supplier. A number of factors went into determining these values:

- If a secondary supplier with enough spare production capacity to make up for the lost capacity of the primary supplier was already in use, the number of days to recover was small.
- If a secondary supplier was qualified but not in use, the days to recovery were somewhat longer.

- If a secondary supplier was in use or qualified and the component being produced was developed to certain specifications specifically for our sponsor company, the days to recovery were even longer.
- If our sponsor company would allow a short-term specification change to a component in order to replace a supplier more quickly, the days to recovery were shortened.

The difference between the inventory days of supply and the days to recover is the period of time over which our sponsor company would be losing revenue from lost sales of the product. In addition to this time period, the revenue at risk for each location from the loss of a supplier was a factor of the revenue from the finished product. For example, the revenue at risk from losing a sewing center which provides 100% of a finished product is 100% of the revenue the company expects to earn from that finished product for the time period where days of inventory cannot cover the days to recovery.

3.3.3. Baseline Probability of Disruption

a. Probability of Disruption Due to Natural Disasters

AIR Worldwide provided us with building damage ratios from catastrophes with specific frequencies of occurrence based on 10,000 stochastic simulations of the following year's activity (Appendix C).

- 20-year event equivalent to 5% annual probability of occurrence
- 50-year event equivalent to 2% annual probability of occurrence
- 100-year event equivalent to 1% annual probability of occurrence
- 250-year event equivalent to 0.4% annual probability of occurrence
- 500-year event equivalent to 0.2% annual probability of occurrence
- 1000-year event equivalent to 0.1% annual probability of occurrence

In conjunction with our sponsor company, we selected a building damage threshold that would equate to the functional loss of a node in the supply chain. We chose 1% building damage as the threshold for a couple of reasons:

1) An industrial site with relatively minor damage would not be allowed to operate by regulatory agencies even if still technically capable of operating.
2) The industrial facilities are relatively well-built when compared to residential buildings. A natural disaster causing 1% damage to an industrial facility would likely cause much more damage to residential buildings and utilities infrastructure, severely affecting the labor force.

Once the damage threshold was selected, we graphed the damage ratio against different probabilities of loss as shown in Figure 9. The figure only shows locations where a single type

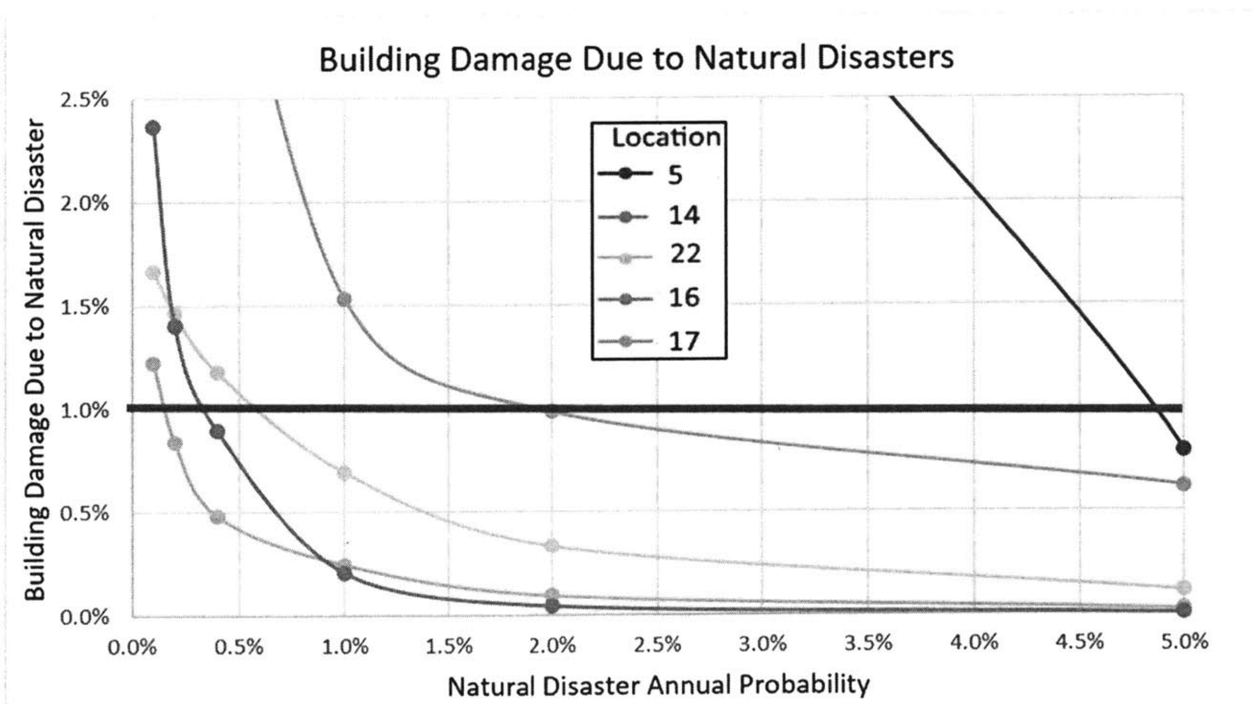

Figure 9. Locations with One Natural Disaster Causing > 1% Building Damage.

of disaster was expected to cause greater than 1% damage. For each location, we equated the annual probability of loss with the annual probability of natural disaster where the building damage sustained was 1%. Figure 10 shows an example of a location where multiple disasters surpassed the 1% building damage threshold for a single location. When this occurred, we first determined the annual probability for the disasters where the building damage was at 1% and then combined them. We assumed the natural disaster events were independent of each other. If the natural disaster events are not independent, combining them as independent will overstate the probabilities. By assuming independence, the probability of any one of the events occurring in a given year could be calculated as:

$$1 - [1\text{-}Pr(Natural\ Disaster_1)] * [1\text{-}Pr(Natural\ Disaster_2)] * \ldots\ldots * [1\text{-}Pr(Natural\ Disaster_N)]$$

From Figure 11, the Cyclone and Earthquake annual probabilities of occurrence cross the 1% building damage threshold at 2.4% and 3.9% respectively. Therefore, the combined probability of natural disaster risk in this location is calculated as 1-(1 – 2.4%)*(1 – 3.9%) = 6.4%.

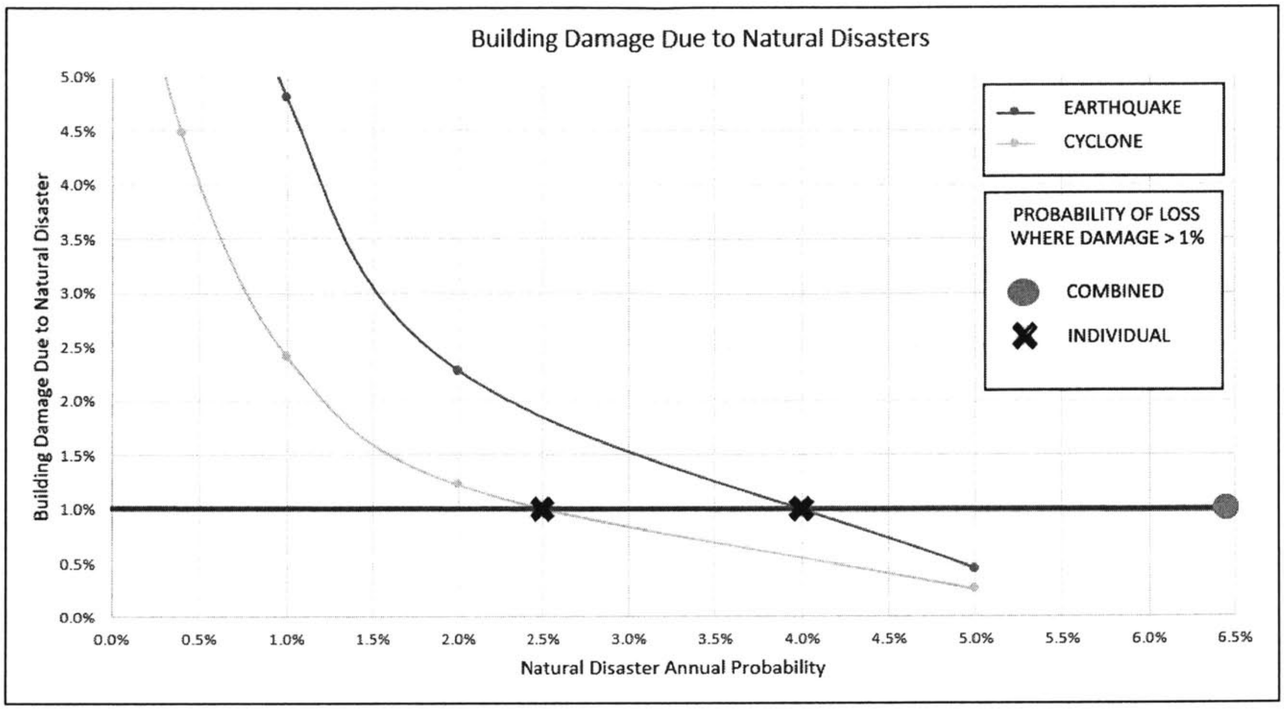

Figure 10. Multiple Natural Disasters Causing > 1% Building Damage at Location 4.

b. Probability of Disruption Due to Geopolitical Events

In order to use the risk index data provided by Verisk Maplecroft, we developed a process to equate the index scores with probabilities of disruption. We relied on insights from Verisk Maplecroft as to how the indices were created as well as input from our sponsor company. For each of the five indices we were provided, Verisk Maplecroft gave us insight into the different datasets they used to create the indices and whether the inputs were qualitative, quantitative, or a combination of the two. They also informed us of the general distribution of the scores within each index and whether the scores were ordinal or nominal. We then considered the significance of what the indices were measuring to the supply chain and the potential disruptions that could occur from a location with a low index score. Given all of these factors, we worked with our sponsor company to create disruption probability curves for each index using an exponential decay model as a basis:

$$N(t) = N_0 e^{-\lambda t}.$$

For each index, we set a maximum value and a constant, λ, which determined the steepness of the curve. We were then able to compute a probability of disruption for geopolitical risk at each node in our sponsor company's supply chain within a year (Appendix B). Using the graph in Figure 11, Figure 12 gives an example of the annual probabilities of loss that would equate to specific risk index values for a supply chain node within a year. Due to the nature of the indices used, the resulting annual probabilities of loss should be viewed as relative values.

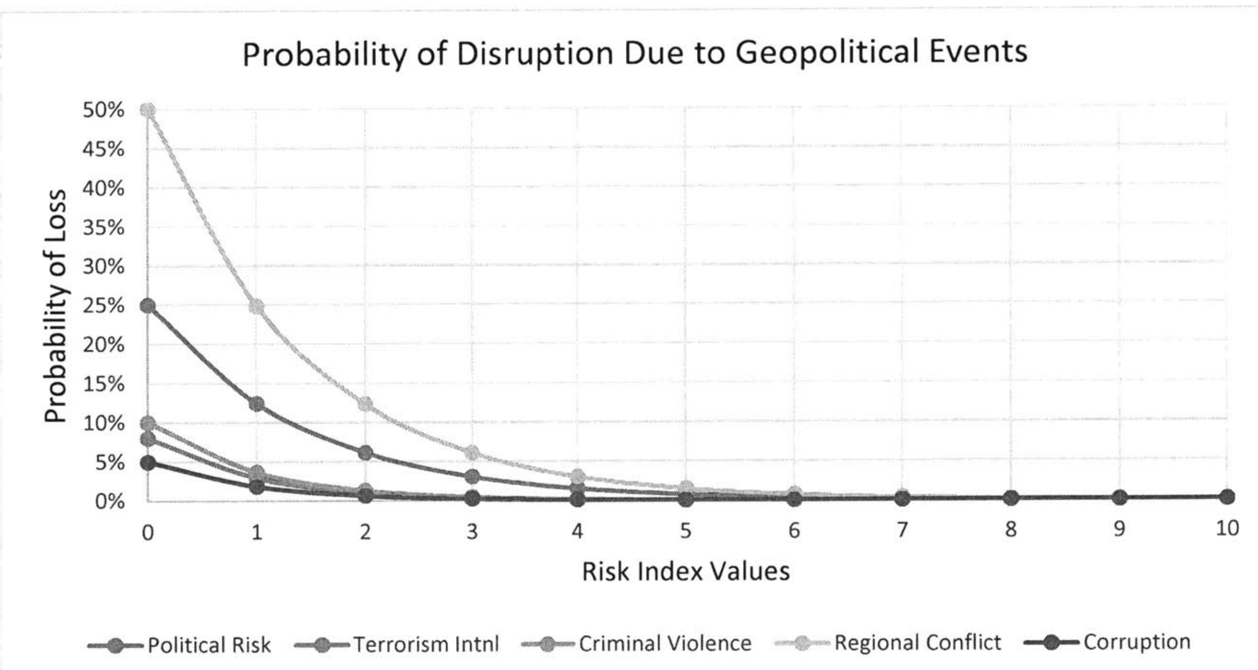

Figure 11. Probability of Disruption Due to Geopolitical Events.

	Political Risk	Terrorism International	Criminal Violence	Regional Conflict	Corruption
Index Value	**1**	**2**	**3**	**4**	**5**
Probability of Loss	12.5%	1.0%	0.5%	4.0%	0.1%

Figure 12. Probabilities of Loss Equated with Different Risk Index Values from Figure 11.

Assuming that the five geopolitical risk indices were independent allowed us to combine the probabilities of disruption from all of the indices using the following equation:

*1 - [1-Pr(Geopolitical Event$_1$)] * [1-Pr(Geopolitical Event$_2$)] * ...... * [1-Pr(Geopolitical Event$_N$)]*

For example, as shown in Figure 12, the annual probability of loss due to geopolitical events for a node with these index values would be 28.9% by following the equation, 1- [(1-12.50%)*(1-1.00%)*(1-0.50%)*(1-4.00%)*(1-0.10%)].

c. Probability of Disruption Due to Supplier Financial Instability

Before Edward Altman develop the Altman Z-Score, William Beaver used a statistical method, t-test, to explore the likelihood of bankruptcy based on a company's financial ratios from sampling various companies. Altman's model was built upon the statistical method for discriminant analysis. In the analysis of James Wahlen and Stephen Baginski (2011), the Z-Score was converted into a probability of bankruptcy by utilizing the normal density distribution function:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

The relationship between the Altman Z-Score and the probability of bankruptcy is displayed in Figure 13. For example, a Z-Score of 2.99 converts into a probability of bankruptcy of 2.33%. The cutoff points for the gray zone are 1.81 to 2.99, which convert to probabilities of bankruptcy of 20.90% to 2.33% respectively.

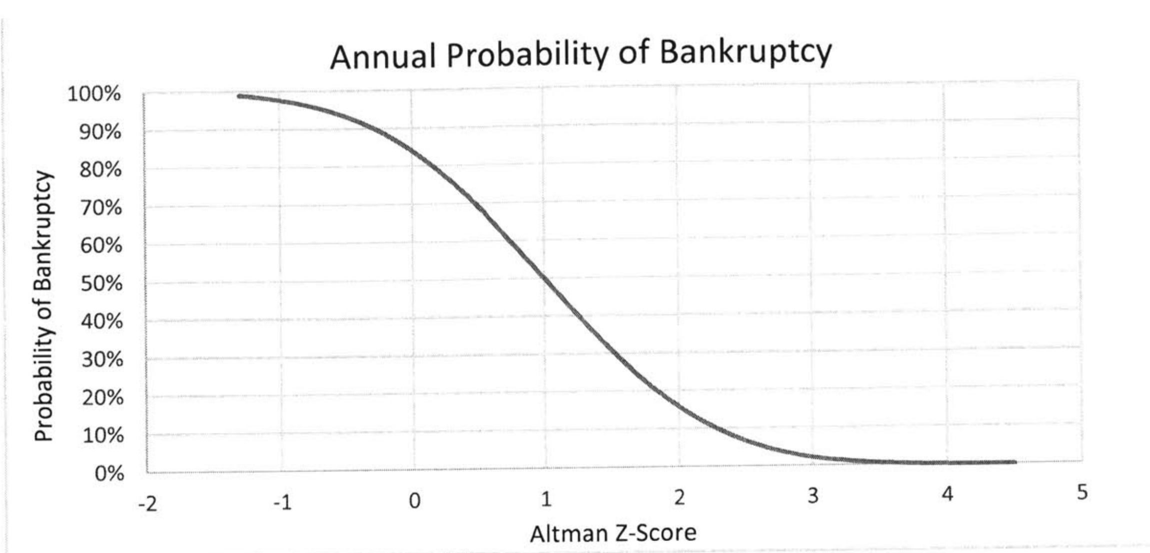

Figure 13. Relationship between Annual Probability of Bankruptcy and Altman Z-Score. (Baginski 2011).

For public companies, we converted the Altman Z score into probability of loss within one year by utilizing the normal density distribution function for the public companies. For private companies, we estimated the annual probability of loss from matrix based on OneSource Business Browser.

According to Altman's report (Altman 1968), the classification accuracy and error rates of the three risk zones of bankruptcy prediction vary by the number of years in the prediction. The forecast of Altman Z score is 95% accurate within one year before bankruptcy, and 83% accurate within the two year before the bankruptcy. We calculated the Z-Scores we received from our sponsor company's data from last year, giving us 95% accuracy. Appendix D contains the probabilities of loss due to bankruptcy that we used in our analysis.

d. Combined Probability of Disruption

To describe the frequency and magnitude of disruptive events in a specific geographic area, we converted the numerical values in the indices to probabilities of supplier loss. This was done in coordination with our sponsor company and the providers of the indices we used. We assumed that the probability of disruption due to natural disasters, geopolitical events, and supplier bankruptcy were independent. Therefore, the probability of disruption from any of the events occurring can be calculated as:

1-[1-Pr(Natural Disaster)][1-Pr(Geopolitical Event)]*[1-Pr(Supplier Bankruptcy)]*

3.4. Risk Visualization

To visualize the risk inherent in our sponsor company's supply chain, we input our data into the software SourceMap. We first mapped the supply chain network for our two representative products. Then, the value-at-risk was overlaid on the supply chain network to give a visual depiction of the risk at each node in the supply chain.

3.4.1. Supply Chain Network Mapping

To map the supply chain network for our two representative products, we gathered a large amount of data from our sponsor company. Utilizing the data which was produced in a report from their enterprise resource planning (ERP) software along with bills of material (BOM) for our representative products, we were able to create a map of the representative products' supply chain networks. We were able to trace the supply chain back to first-tier and, in some cases, second-tier suppliers (Figure 14). Because the materials used in garment manufacturing are not very complex, tracing the supply chain back any further than second-tier suppliers was not feasible.

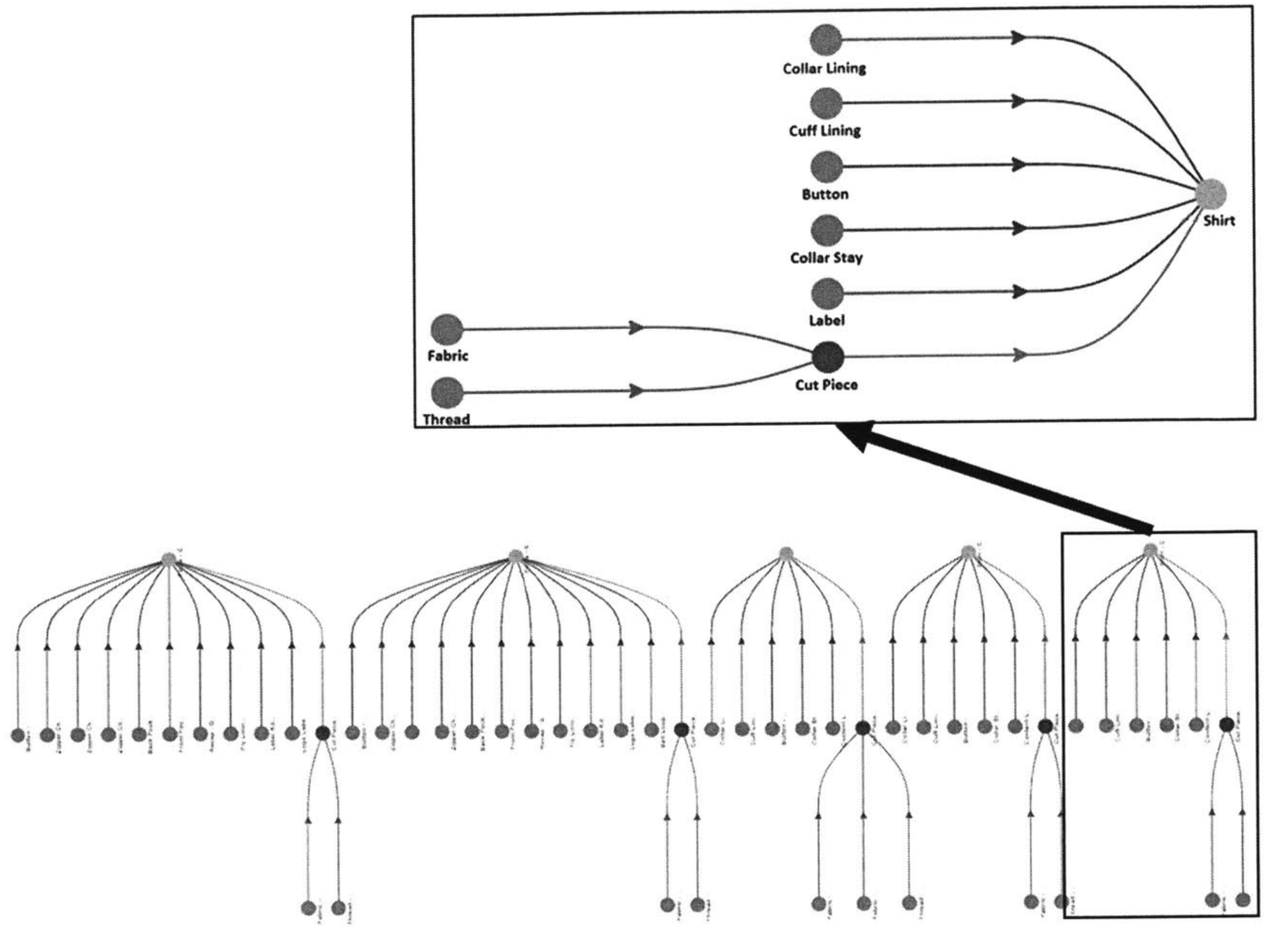

Figure 14. Upstream Supply Chain Network with Blow-Up Insert.

3.4.2. Value-at-Risk Mapping

Utilizing the SourceMap software, the values-at-risk we calculated were overlaid on a visual representation of the two supply chain networks we mapped. In addition to value-at-risk, the inventory days of supply, days to recovery, and revenue at risk were also represented at each supply chain node in SourceMap. The nodes in the supply chain were color-coded according to the magnitude of their corresponding value-at-risk.

3.5. Risk Management

Visualizing risk in a supply chain is a tool for better decision-making when it comes to managing supply chain risk. By mapping the flow of components and finished products in a supply chain as well as the value-at-risk at each node, supply chain managers have a tool to better inform their sourcing, production, and risk mitigation decisions. Once the risk in the supply chain was visualized, risk management efforts were focused on nodes where value-at-risk was high relative to other nodes. Since all of the factors going into the value-at-risk calculation were also depicted on the SourceMap output, the cause of the high value-at-risk could be easily investigated. Risk management decisions could be made to increase inventory days of supply, decrease the days to recovery, or institute dual sourcing for specific components. These opportunities to reduce the value-at-risk at nodes in their supply chain were discussed with our sponsor company.

4. ANALYSIS AND RESULTS

We selected a small number of representative products and mapped the value-at-risk in their upstream supply chains. The resulting value-at-risk was affected by the three different combined loss probabilities at each location. We evaluated the contribution of each of these risk categories to the value-at-risk at each location and within the overall supply chain's value-at-risk. From the SourceMap value-at-risk visualization, we looked more closely at the supply chain nodes with relatively high risk. From this analysis, we determined ways to lower the value-at-risk at these locations. In the discussion section, we address some alternative risk mitigation scenarios for the high risk locations.

4.1. Probability of Loss

The probabilities of loss used to determine the value-at-risk at each supply chain node were a factor of the financial, natural disaster, and geopolitical risks. For the nodes we evaluated, Figure 15 shows the contribution of each of the three risk categories to the overall probability of loss we used for the individual supply chain nodes.

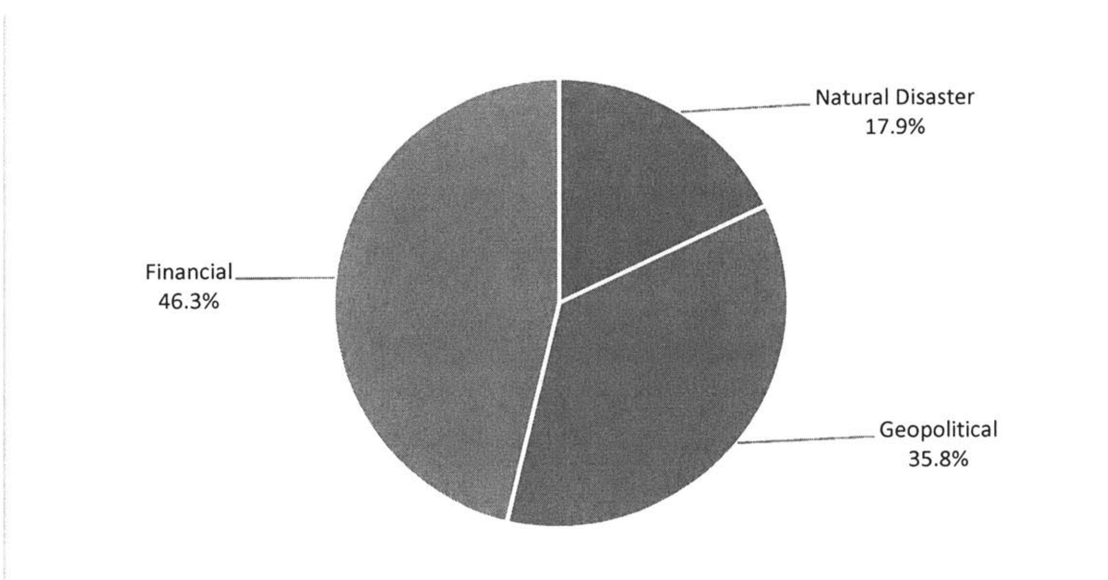

Figure 15. Risk Category Contribution to Probability of Loss.

Although the probabilities of loss were arrived at quantitatively, they are estimates based on a combination of qualitative and quantitative data alongside input from our sponsor company. The strength is in their relative values. Figure 16 shows a distribution of their relative values while Figure 17 shows the geographic distribution of the different baseline probabilities of loss.

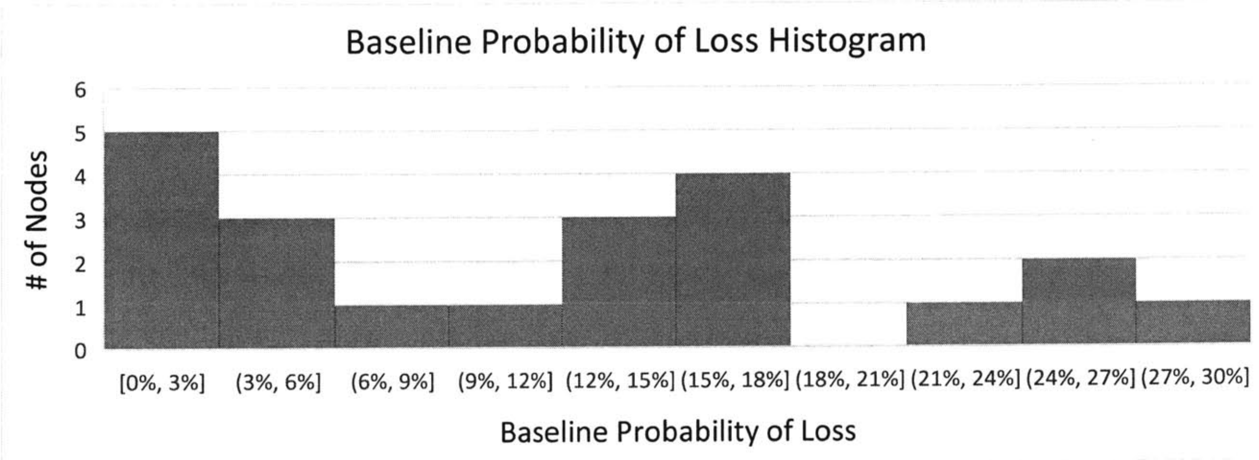

Figure 16. Distribution of Probability of Loss Values.

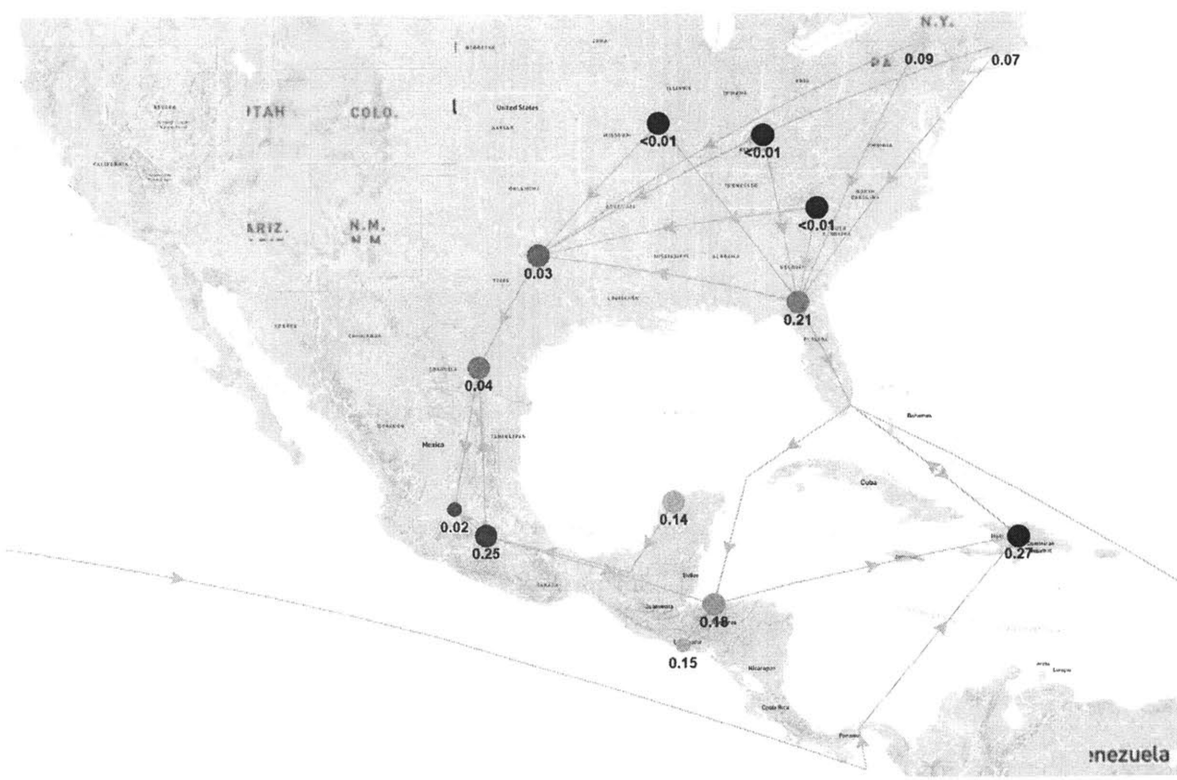

Figure 17. Baseline Probability of Loss.

4.2. Value-at-Risk

When combining the probability of loss with other factors at each supply chain node in SourceMap, we arrived at a value-at-risk. Two of these other factors were inventory days of supply and time to recovery. The differences between the inventory days of supply and time to recovery determined the length of a potential disruption at each node in the supply chain. The recovery times are mapped in Figure 18. A potential length of disruption exists at each node for each component. These values are graphed below in Figure 19.

Figure 18. Recovery Time in Days.

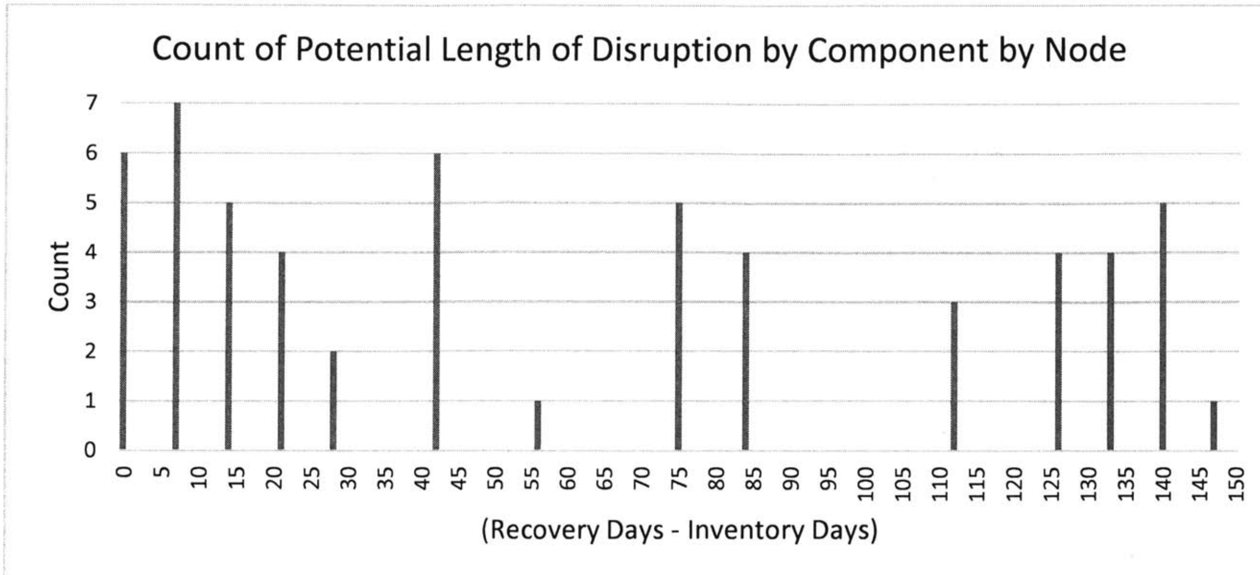

Figure 19. Potential Length of Disruptions.

The length of a potential disruption multiplied by the revenue at risk determined the risk exposure index values seen in Figure 20. By multiplying the risk exposure index values by the baseline probabilities of loss, we calculated a value-at-risk for each location (Figure 21).

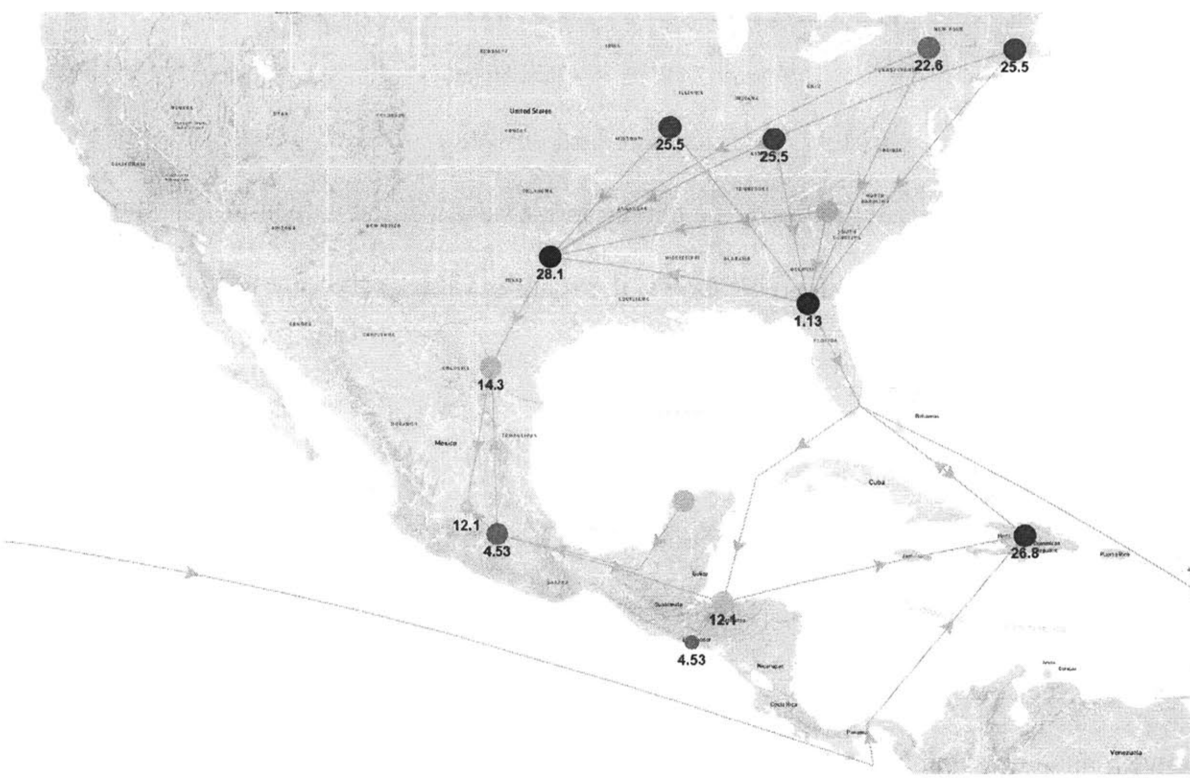

Figure 20. Risk Exposure Index ($M).

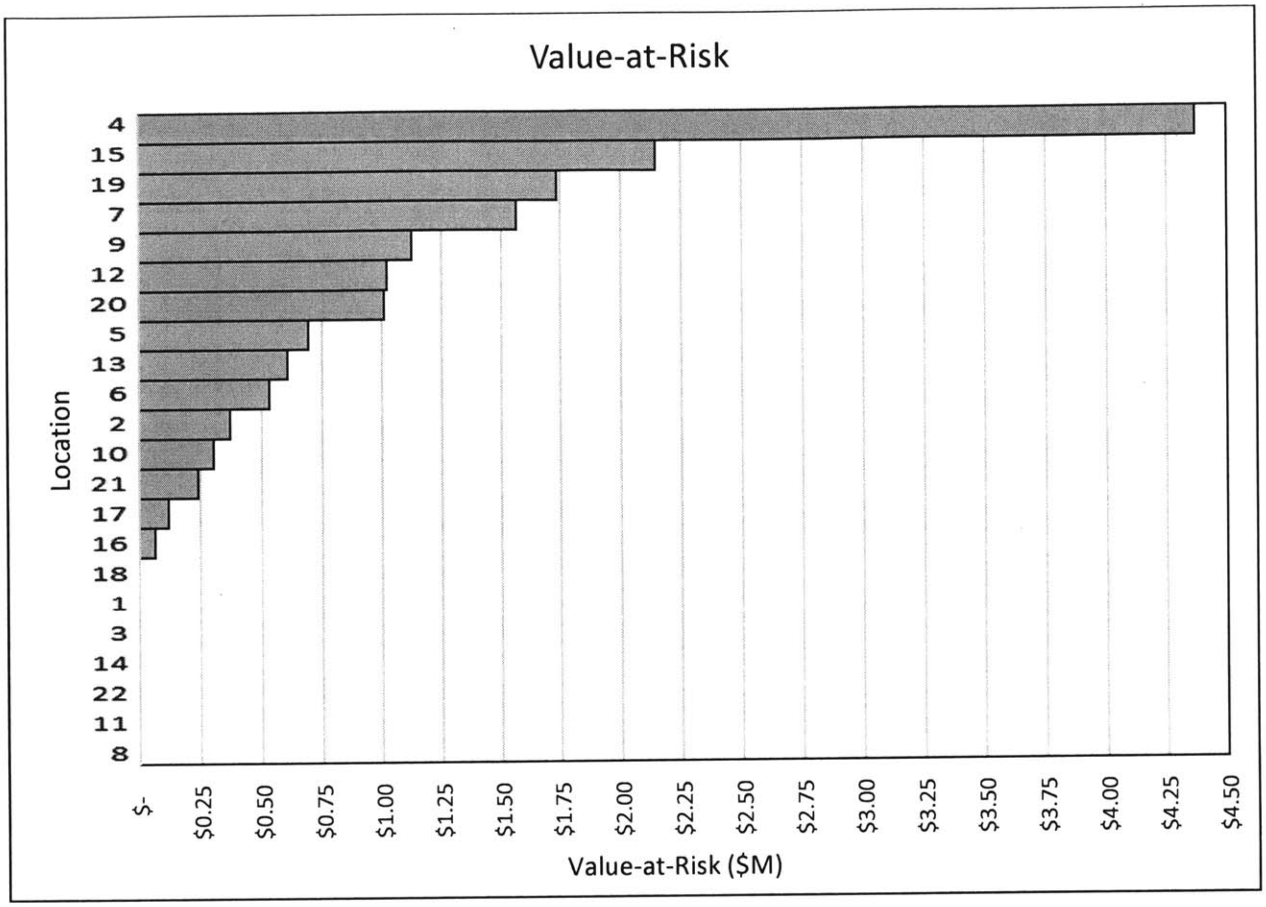

Figure 21. Value-at-Risk Statistics.

The values ranged from $0-$4.37 M with a standard deviation of $1.03 M. Because of the assumptions made in the calculations, the actual dollar values of the values-at-risk should be treated with suspicion; but, as the data shows, the relative values can point to the riskier nodes in the supply chain.

4.3. Risk Visualization

In order to visualize the risk in our sponsor company's supply chain, we utilized SourceMap to overlay the value-at-risk for each node in the supply chain on a geographic depiction of their supply chain. Figure 22 and Figure 23 show the geographic depictions of the supply chain at a global and regional scale respectively. Figure 24 shows the final risk visualization product.

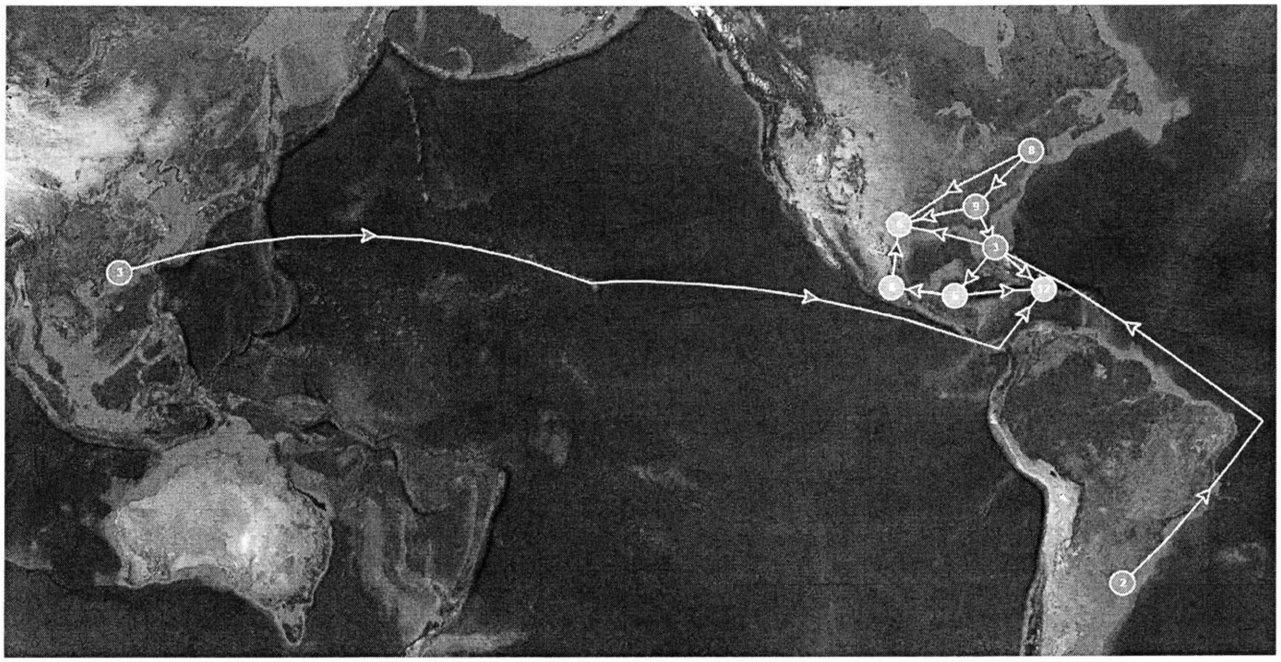

Figure 22. Global Scale of Supply Chain Network.

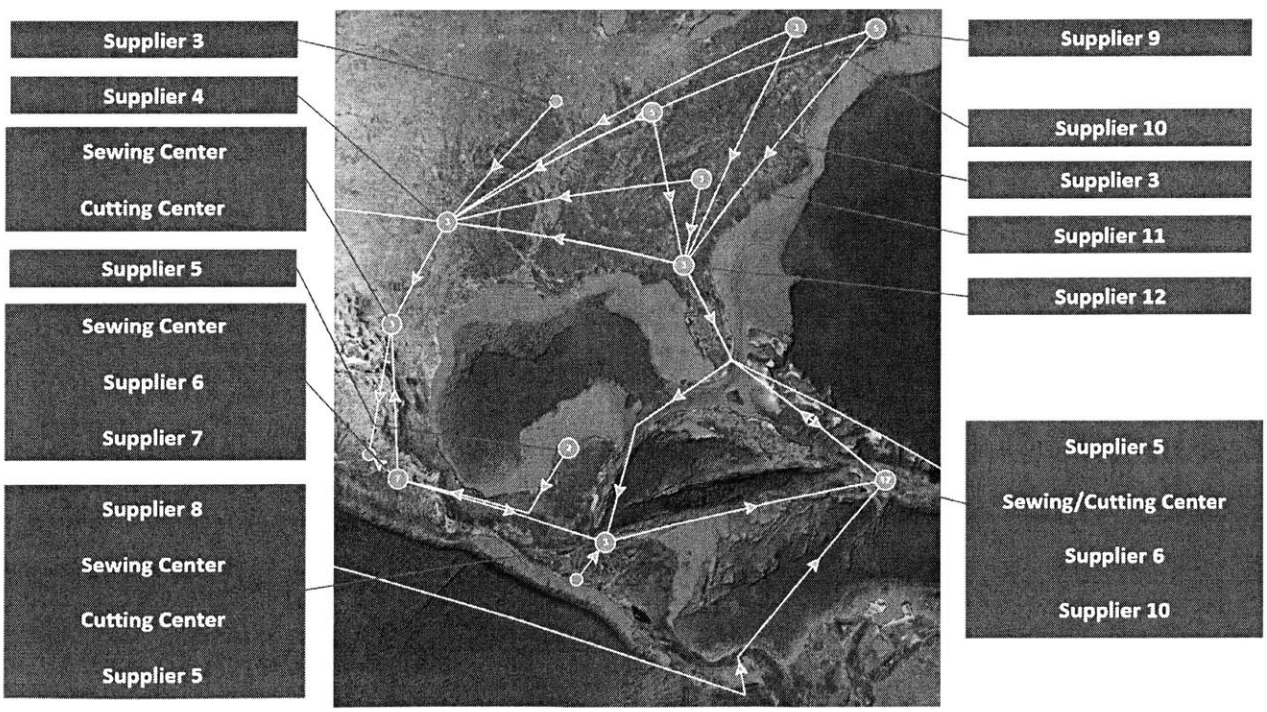

Figure 23. Regional Concentration of Supply Chain Network.

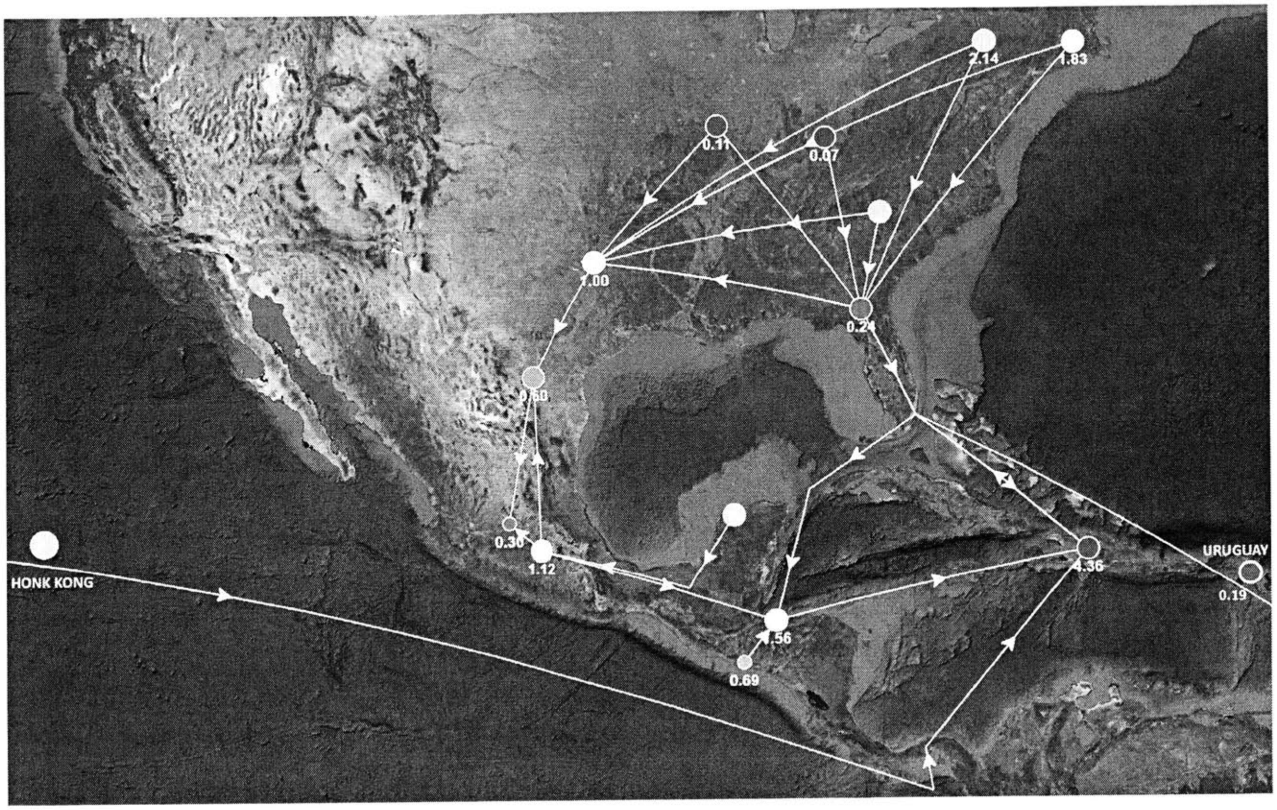

Figure 24. Value-at-Risk ($M).

In our use of SourceMap, we focused on estimating the risks at the nodes. Actual transportation flows do not travel directly from node to node but follow various routes. As shown in Figure 25, waypoints can be added in SourceMap between nodes to more accurately depict the flow of raw materials through the supply chain. While there is no value-at-risk calculated at these waypoints, an accurate visual depiction of the supply chain is still important for companies to identify critical geographic points. Companies with a high volume of product or raw materials passing through a single port or border crossing should closely monitor disruptions at these locations and plan alternate transportation routes in case of disruption. In order to calculate a risk exposure index at critical transit links, a recovery time for the link of interest would have to be estimated.

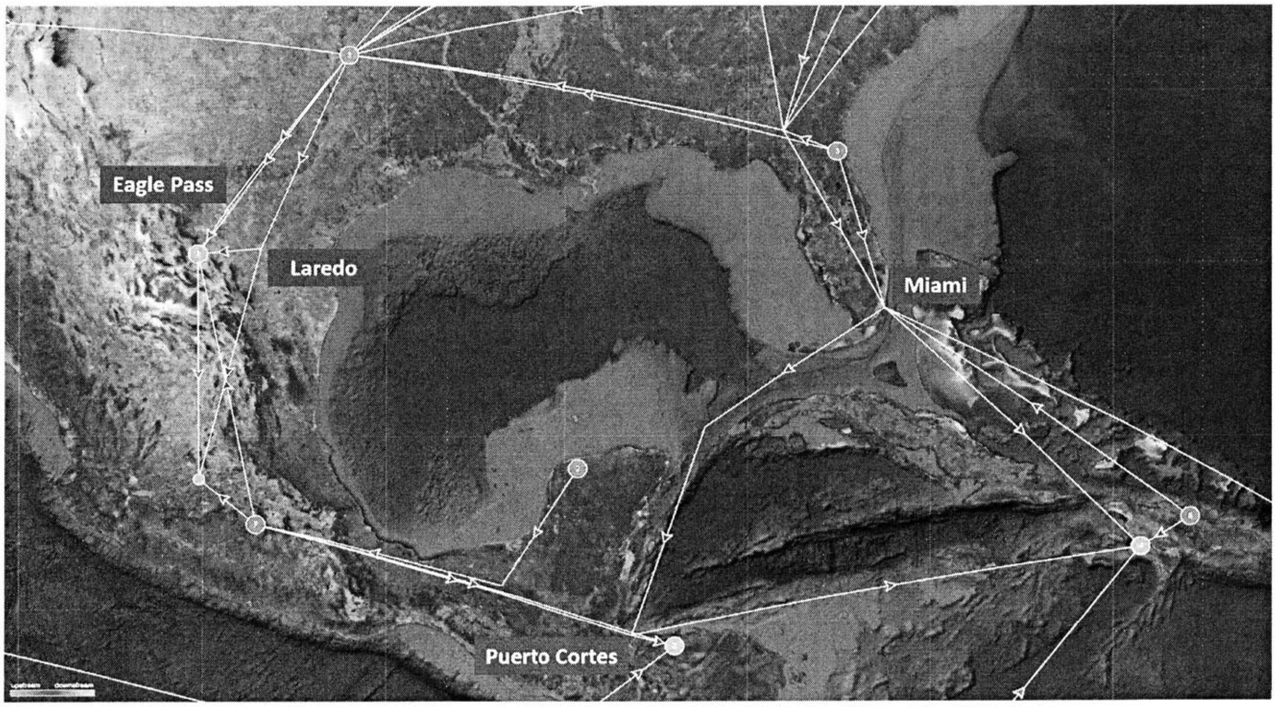

Figure 25. Waypoints Selected for More Accurate Visualization of Supply Chain Network.

4.4. Risk Mitigation

We conducted a root cause analysis at the supply chain nodes with the highest value-at-risk. Locations 4 ,15, and 19 had the highest values-at-risk with \$4.37M, \$2.15M, and \$1.74M respectively. The root causes analysis allowed us to identify the main contributors to the elevated value-at-risk. Figure 26 shows the contributors to the value-at-risk at the nodes we selected. Identifying the main contributors to the value-at risk allowed us to implement strategies for mitigating the risk and run additional analysis.

Location	Recovery Days	Inventory Days of Supply	Revenue ($M)	Sourcing Split	Baseline Probability of Loss	Baseline Probability of Loss Contributed to.. Natural Disaster	Geopolitical	Financial
4	168	28	140	100%	16.27%	6.70%	0.63%	8.93%
15	168	28	177	100%	9.48%	0.00%	0.14%	9.34%
19	168	42	317	100%	7.19%	7.01%	0.14%	0.04%

Figure 26. Contributors to Value-at-Risk at Selected Nodes.

4.4.1 Mitigation Scenario 1

At Location 4, we found that the relatively high value-at-risk is partially a result of the long recovery time, 168 days. We chose to mitigate this risk by decreasing the number of recovery days to the average number of recovery days for all of our sponsor company's suppliers, 82 days. The reason the number of recovery days is currently high is due to the lengthy supplier qualification process. If a backup supplier was prequalified or the specifications for the component were changed, cutting the recovery time in half is reasonable. If the recovery time was decreased to 82 days, the new value-at-risk at Location 4 would be reduced by 61% to $1.69M.

4.4.2 Mitigation Scenario 2

At Location 15, we found that the relatively high value-at-risk is partially a result of the high length of potential disruption, 140 days. We chose to mitigate this risk by increasing the amount of safety stock to 60 days of supply. If the safety stock was increased to 60 days of supply, the new value-at-risk at Location 15 would be reduced by 23% to $1.66M. The increased safety stock would come with increased inventory costs. A decision would have to be made as to whether or not the trade-off in decreased value-at-risk is worth it.

4.4.3 Mitigation Scenario 3

At Location 19, we found that the relatively high value-at-risk is partially a result of the amount of revenue at risk, $317M. All five of the product groups that we evaluated rely on the supplier at this location for a component. The supplier at Location 19 is the single-source supplier for this component. By introducing dual-sourcing for this component, reliance on this supplier can be decreased. With a 50% sourcing split, the value-at-risk at this location is reduced by 50% to $0.87M.

Also at Location 19, 97% of the baseline probability of loss is due to the natural disaster risk. According to AIR Worldwide's catastrophe modeling at this location, the supplier has a high risk of disruptive damage due to flooding. We would encourage our sponsor company to ensure the supplier has proper flood risk mitigation measures in place.

5. DISCUSSION

In our thesis, we developed an approach to combine different categories of risk that were of interest to our sponsor company. To do this, we relied on companies and tools such as AIR Worldwide, Verisk Maplecroft, and the Altman Z-Score. We showed how risk information from a variety of sources could be used to create relative values-at-risk for comparative purposes. In the case of our sponsor company, we focused on a small number of product groups and mapped their supply chain. The values-at-risk, combined with the visual depiction of the supply chain, provided a tool for risk mitigation.

5.1. Risk Visualization

Due to the complexity of global supply chains, a visual depiction is a valuable tool. A clear view of the supply chain network and where risk resides in the network can be gained from Figure 22, Figure 23, and Figure 24 found in Section 4.3. Whereas, solely looking at the vast amount of data we used to create the visualizations is overwhelming and un-insightful.

5.2. Risk Mitigation

In Section 4.4, we looked at potential ways to mitigate risk at specific supply chain nodes. Given our results, we feel the risk visualization tool we created can be used by our sponsor company to target and lower areas of elevated supply chain risk.

5.3. Limitations

In order to complete our project, a number of simplifying assumptions were made. Assumptions were made due to time and data constraints.

- In order to simplify our calculation of the risk exposure index, we assumed that events were either non-disruptive or totally disruptive to the supply chain. Therefore, the recovery days would be the amount of time that our sponsor company needed to find an alternative source to resume supply of the affected components.

- The risk indices for geopolitical events were created at the national level. Since the conditions measured by these indices would vary across a country, a more localized dataset would give a clearer picture of the effect of these conditions on supply chain disruption. For smaller countries, the country-level datasets have more meaning.
- Some private companies publish very limited financial information. Because of this, calculating their Altman Z-Scores was not possible unless our sponsor company was able to provide us with all of the necessary inputs from their private suppliers.
- When we combined the probabilities of loss from different types of natural disasters, we assumed the events were independent.
- When we combined the probabilities of loss from different geopolitical events, we assumed the different events were independent.
- When we calculated the value-at-risk within our sponsor's supply chain network, we only focused on the nodes where components were sourced or produced and not on any transit points such as ports or border crossings.

6. CONCLUSION

Supply chains are exposed to a variety of risks as they become more complex and geographically diverse. Disruptions due to these risks can be costly. Companies cannot hope to mitigate all of their supply chain risks. In order to focus risk management resources on locations in the supply chain with the most risk, companies need a comprehensive method to quantify all of their significant supply chain risks.

A multitude of different risks can potentially affect a company's supply chain. While it may not be feasible to model the effects of all these risks, companies can make a determination as to which risks most concern them. In our case, these risks to supply chain disruption were natural disasters, geopolitical events, and supplier bankruptcy. Our thesis showed that different categories of risks can be combined to present a comprehensive picture of relevant risk throughout a company's supply chain network.

By quantifying and visualizing the values-at-risk across the supply chain, an effective risk mitigation tool can be built. Our results showed that specific high risk nodes in a company's supply chain can be easily identified with this risk mitigation tool. Once identified, mitigation measures such as dual sourcing, increased safety stock, and reduced recovery time can significantly reduce the value-at-risk. While the tool we built is specific to our sponsor company, other companies in other industries could apply a similar approach to build an organizational risk management tool.

6.2. Further Research

There were a number of areas that were either outside the scope of what we were trying to achieve during this project or that were unable to be explored due to limitations on time and resources. We recommend the following areas of further research.

- Our research assumed all events were independent because we did not have enough information on the correlation of disruptive events. Future studies could seek to identify conditional probabilities for the different types of disruptive events we used in our analysis.
- The geopolitical event risk indices are country-wide indices. Further research could be done to identify or create similar indices for more specific locations or industries.
- The bankruptcy forecasts from the Altman Z-Score have various accuracy levels depending on the number of years into the future they are attempting to predict bankruptcy. Further research could be done to incorporate the accuracy percentage of the model into the probability of loss values.
- Sensitivity analysis could be conducted to find the correlation between the probability of bankruptcy and the factors we used to determine the probability of bankruptcy for private companies.
- When we converted the natural disaster risk indices into annual probabilities of occurrence, we graphed each risk index to estimate the probability of occurrence at the selected building damage threshold. However, we were only provided with point data and the data was not continuous. Further research could seek to create a series of curves plotting building damage and likelihood of occurrence from which data could be extracted without estimation.
- The conversion of the geopolitical event index values to probabilities of loss was based on discussion with our sponsor company and Verisk Maplecroft. Further research could explore the relationship between the likelihood of supply chain disruption and the risk factors quantified by each index.

APPENDICES

Appendix A – Verisk Maplecroft Risk Index Data

Location	Political Risk	Terrorism Intnl	Criminal Violence	Regional Conflict	Corruption
1	8.36	9.11	8.97	10	8.76
2	6.77	9.68	3.46	10	4.05
3	6.77	9.68	3.46	10	4.05
4	6.77	9.68	3.46	10	4.05
5	7.2	10	1.9	10	4.46
6	5.4	10	2.9	10	2.16
7	5.73	10	0.28	10	2.1
8	5.73	10	0.28	10	2.1
9	7.08	9.76	0.99	10	2.84
10	7.08	9.76	0.99	10	2.84
11	7.08	9.76	0.99	10	2.84
12	7.08	9.76	0.99	10	2.84
13	7.08	9.76	0.99	10	2.84
14	7.08	9.76	0.99	10	2.84
15	7.7	9.99	6.72	10	9.03
16	8.3	6.63	7.06	10	8.99
17	8.3	6.63	7.06	10	8.99
18	8.3	6.63	7.06	10	8.99
19	8.3	6.63	7.06	10	8.99
20	8.3	6.63	7.06	10	8.99
21	8.3	6.63	7.06	10	8.99
22	8.3	6.63	7.06	10	8.99

Appendix B - Probability of Loss Due to Geopolitical Events

Location	Political Risk $Pr(Loss)_1$	Terrorism Intnl $Pr(Loss)_2$	Criminal Violence $Pr(Loss)_3$	Regional Conflict $Pr(Loss)_4$	Corruption $Pr(Loss)_5$	Total Pr(Loss)
1	0.07%	0.00%	0.00%	0.05%	0.00%	0.12%
2	0.22%	0.00%	0.31%	0.05%	0.09%	0.66%
3	0.22%	0.00%	0.31%	0.05%	0.09%	0.66%
4	0.22%	0.00%	0.31%	0.05%	0.09%	0.66%
5	0.16%	0.00%	1.50%	0.05%	0.06%	1.76%
6	0.57%	0.00%	0.55%	0.05%	0.58%	1.73%
7	0.45%	0.00%	7.56%	0.05%	0.61%	8.58%
8	0.45%	0.00%	7.56%	0.05%	0.61%	8.58%
9	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
10	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
11	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
12	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
13	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
14	0.18%	0.00%	3.72%	0.05%	0.29%	4.21%
15	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
16	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
17	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
18	0.11%	0.00%	0.01%	0.05%	0.00%	0.17%
19	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
20	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
21	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%
22	0.07%	0.01%	0.01%	0.05%	0.00%	0.14%

Appendix C - AIR Worldwide Catastrophe Modeling Data

Exposure Information		Building Damage Ratio						
		Annual Average	5.0%	2.0%	1.0%	0.4%	0.2%	0.1%
Location	Peril	AAL(EV)	20	50	100	250	500	1,000
1	Tropical Cyclone	0.02%	0.08%	0.13%	0.19%	0.29%	0.39%	0.47%
2	Earthquake	0.17%	0.47%	2.21%	4.67%	9.03%	15.07%	16.78%
2	Tropical Cyclone	0.11%	0.35%	1.35%	2.75%	4.94%	8.47%	12.44%
3	Earthquake	0.16%	0.44%	2.27%	4.80%	8.19%	12.26%	16.47%
3	Tropical Cyclone	0.09%	0.26%	1.22%	2.41%	4.48%	6.29%	11.99%
4	Earthquake	0.16%	0.43%	2.14%	4.96%	8.51%	12.06%	15.37%
4	Tropical Cyclone	0.12%	0.39%	1.60%	2.96%	5.33%	9.47%	11.99%
5	Earthquake	0.37%	0.79%	5.15%	12.49%	22.92%	26.72%	29.46%
5	Tropical Cyclone	0.00%	0.00%	0.00%	0.01%	0.02%	0.07%	0.19%
7	Earthquake	0.03%	0.00%	0.00%	0.02%	0.07%	0.31%	6.22%
7	Tropical Cyclone	0.28%	0.64%	3.33%	7.98%	16.58%	22.70%	29.71%
8	Tropical Cyclone	0.02%	0.01%	0.12%	0.54%	1.27%	2.22%	3.74%
8	Earthquake	0.05%	0.00%	0.02%	0.18%	1.84%	4.75%	12.29%
12	Earthquake	0.04%	0.00%	0.00%	0.28%	0.71%	5.38%	15.51%
12	Tropical Cyclone	0.02%	0.08%	0.41%	0.51%	0.68%	0.84%	1.02%
13	Earthquake	0.00%	0.00%	0.00%	0.00%	0.11%	0.42%	0.83%
13	Tropical Cyclone	0.01%	0.01%	0.27%	0.39%	0.52%	0.63%	0.73%
14	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
14	Tropical Cyclone	0.13%	0.62%	0.99%	1.53%	3.81%	5.38%	8.18%
9	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.14%	0.31%
9	Tropical Cyclone	0.01%	0.02%	0.27%	0.38%	0.51%	0.64%	0.81%
10	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
10	Tropical Cyclone	0.00%	0.00%	0.02%	0.12%	0.30%	0.38%	0.60%
11	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
11	Tropical Cyclone	0.00%	0.00%	0.00%	0.03%	0.12%	0.23%	0.38%
19	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
19	Inland Flood	0.02%	0.07%	0.26%	0.46%	0.53%	0.60%	0.60%
19	Tropical Cyclone	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.03%
19	Severe Thunderstorm	0.00%	0.00%	0.01%	0.02%	0.10%	0.19%	0.36%
19	Winterstorm	0.00%	0.01%	0.02%	0.03%	0.05%	0.06%	0.10%
20	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
20	Inland Flood	0.02%	0.12%	0.38%	0.48%	0.50%	0.51%	0.51%
20	Tropical Cyclone	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.07%
20	Severe Thunderstorm	0.01%	0.01%	0.03%	0.09%	0.28%	0.55%	0.90%
20	Winterstorm	0.00%	0.01%	0.01%	0.01%	0.02%	0.06%	0.17%
22	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.24%	0.93%
22	Inland Flood	0.01%	0.07%	0.11%	0.11%	0.14%	0.14%	0.14%

Exposure Information		Building Damage Ratio						
		Annual Average	5.0%	2.0%	1.0%	0.4%	0.2%	0.1%
Location	Peril	AAL(EV)	20	50	100	250	500	1,000
22	Winterstorm	0.00%	0.01%	0.02%	0.03%	0.05%	0.06%	0.13%
18	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.45%
18	Inland Flood	7.69%	78.79%	90.70%	94.08%	96.83%	98.13%	99.00%
18	Tropical Cyclone	0.00%	0.00%	0.01%	0.03%	0.18%	0.43%	0.89%
18	Severe Thunderstorm	0.00%	0.00%	0.00%	0.01%	0.03%	0.11%	0.24%
18	Winterstorm	0.01%	0.01%	0.02%	0.03%	0.05%	0.10%	0.16%
16	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
16	Inland Flood	0.03%	0.24%	0.31%	0.31%	0.31%	0.31%	0.31%
16	Tropical Cyclone	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%	0.06%
16	Severe Thunderstorm	0.04%	0.11%	0.33%	0.69%	1.18%	1.47%	1.67%
16	Winterstorm	0.00%	0.01%	0.01%	0.02%	0.04%	0.08%	0.09%
17	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
17	Inland Flood	0.01%	0.02%	0.07%	0.19%	0.63%	0.63%	0.66%
17	Tropical Cyclone	0.01%	0.01%	0.05%	0.21%	0.90%	1.41%	2.37%
17	Severe Thunderstorm	0.01%	0.01%	0.02%	0.05%	0.14%	0.24%	0.36%
17	Winterstorm	0.00%	0.02%	0.02%	0.03%	0.04%	0.05%	0.05%
21	Earthquake	0.00%	0.00%	0.00%	0.00%	0.00%	0.28%	0.56%
21	Inland Flood	0.01%	0.05%	0.23%	0.26%	0.28%	0.29%	0.29%
21	Tropical Cyclone	0.00%	0.00%	0.01%	0.01%	0.04%	0.11%	0.27%
21	Severe Thunderstorm	0.01%	0.01%	0.03%	0.10%	0.22%	0.39%	0.57%
21	Winterstorm	0.01%	0.01%	0.05%	0.06%	0.08%	0.09%	0.09%

Appendix D - Financial Probability of Loss

Supplier	Adjusted Z-Score	Bankruptcy Probability	Risk Propensity	Spending Rate	Company Size (Employees)	Type
1	2.9	2.87%	Low	N/A	3500	Private Subsidiary
2	4.21	0.07%	Low	Stable	11000	Private Parent
3	1.81	21.15%	N/A	N/A	N/A	Private Independent
4	3.14	1.62%	N/A	Stable	37453	Private parent
5	2.9	2.87%	Low	N/A	3500	Private Subsidiary
6	2.99	9.35%	Moderate	Stable	11000	Private Subsidiary
7	3.95	0.16%	Low	N/A	200	Private Subsidiary
8	4.35	0.04%	Low	Stable	50	Private Branch
9	5.94	0.00%	N/A	N/A	200	Private Independent
10	1.77	22.06%	N/A	Stable	155	Public Independent
11	2.99	9.35%	Moderate	Stable	11000	Private Subsidiary
12	2.99	9.35%	Low	Stable	10	Private Subsidiary
13	2.4	14.07%	Moderate	Stable	8	Private Independent
14	2.99	9.35%	Moderate	Stable	11000	Private Subsidiary
15	2.99	9.35%	Low	Stable	110	Private Branch
16	2.99	9.35%	Moderate	Stable	11000	Private Subsidiary
17	1.77	22.06%	N/A	Stable	155	Private Branch
18	1.81	21.15%	N/A	Stable	600	Private Branch
19	3.62	0.44%	N/A	Stable	45789	Public-Parent

Given	
Calculated	

Appendix E - SourceMap Input Template

PROCESS DATA

Upstream Data Template

Sort Order	BOM-Level	Part Number	Part Name - Description	Harmonized Code	BOM Qty	Unit of Measure	Source-Name	Raw Material Source Split%	Inventory Days of Supply	Finished Good Indicator	Where-Made Street Address	Where-Made-City	Where-Made-Postal-Code	Where-Made-Country	Recovery-Time Days	Forecast in Dollars $M	Port of Exit	Port of Entry	Risk Exposure Index $M	Baseline Probability of Supplier Loss	Value at Risk $M
1	0	A	Carburetor GX	84099111	1.00	EA	PLANT1	100%	10	1	520 2nd St SE	Minneapolis	USA	55414	70	32	Norfolk, VA		5.26	1.00%	0.0526
2	1	D	Float GX	84099192	2.00	EA	CM1	100%	20	1	1122 Queen Street East	Toronto	CAN	M4M 1K	30				0.88	1.00%	0.0088
3	1	E	Body Std	84099192	1.00	EA	CM5	100%	5	1	Ana María Sánchez 213a	Guadalajara	MEX	44810	85				7.01	5.00%	0.3505
4	2	F	Top Cover Std	84099192	1.00	EA	CM4	100%	14	1	Industria Minera 503a	Toluca	MEX	50010	50				3.16	5.00%	0.158
5	2	G	Float Chamber Std	84099192	2.00	EA	CM7	100%	14	1	Nuva Amsterdam 4116a	Monterrey	MEX	64310	90				6.66	5.00%	0.333
6	1	H	Needle Valve GX	84099192	1.00	EA	VEN1	70%	5	1	1011 SW Klickitat Way	Seattle	USA	98134	10				0.31	1.00%	0.0031
7	1	H	Needle Valve GX	84099192	1.00	EA	VEN2	30%	10	1	1911 66 Ave NW	Edmonton	CAN	T6P 1M5	25				0.39	1.00%	0.0039
8	0	B2	Carburetor LX	84099111	1.00	EA	PLANT2	100%	10	2	17-18 French Church Street, Huguenot Quarter	Cork	IRE		80	36	Cork, Ireland		6.9	1.00%	0.069
9	1	I	Float LX	84099192	1.00	EA	CM2	100%	20	2	Persveien 20	Oslo	NOR	0614	40		Oslo, Norw	Cork, Ireland	1.97	2.00%	0.0394
10	1	J	Piston LX	84099192	1.00	EA	CM6	100%	25	2	92 Audley Street	Reading	ENG	RG30 1B	70		Liverpool,	Cork, Ireland	4.44	1.00%	0.0444
11	1	E	Body Std	84099192	1.00	EA	CM5	100%	5	2	Ana María Sánchez 213b	Guadalajara	MEX	44810	85		Manzanillo,	Cork, Ireland	7.89	5.00%	0.3945
12	2	F	Top Cover Std	84099192	1.00	EA	CM4	100%	30	2	Industria Minera 503b	Toluca	MEX	50010	50				1.97	5.00%	0.0985
13	2	G	Float Chamber Std	84099192	1.00	EA	CM7	100%	10	2	Nuva Amsterdam 4116b	Monterrey	MEX	64310	90				7.89	5.00%	0.3945
14	0	B3	Carburetor LX	84099111	1.00	EA	PLANT3	100%	10	3	2丁目-3-6 Akasaka Minato	Tokyo	JAP	107-0052	50	20	Tokyo, Japan		2.19	5.00%	0.1095
15	1	I	Float LX	84099192	1.00	EA	CM3	100%	14	3	Guro-dong, Guro-gu	Seoul	KOR	826-1	30		Seoul, Kore	Tokyo, Japan	0.88	4.00%	0.0352
16	1	J	Piston LX	84099192	1.00	EA	CM8	100%	7	3	300 Beach Road	Singapore	SNG	199555	45		Singapore	Tokyo, Japan	2.08	2.00%	0.0416
17	1	E	Body Std	84099192	1.00	EA	VEN3	100%	14	3	81号 Jingtian Road, Futian	Shenzhen	CHI	518034	70		Shekou, Ch	Tokyo, Japan	3.07	3.00%	0.0921
18	2	F	Top Cover Std	84099192	1.00	EA	VEN4	100%	21	3	448号 Dongfeng Middle Road	Guangzhou	CHI	510030	65				2.41	3.00%	0.0723
19	2	G	Float Chamber Std	84099192	1.00	EA	VEN5	100%	7	3	Graphite India Rd, Hudi	Bengaluru	IND	560048	50		Chennai, In	Shekou, Chi	2.36	4.00%	0.0944
20	0	C	Carburetor VX	84099111	1.00	EA	PLANT4	100%	10	4	Calle 14 # 10-11	Bogota	COL		90	44	Cartagena, Colombia		9.64	2.00%	0.1928
21	1	K	Air Valve Assy VX	84099192	2.00	EA	CM4	100%	7	4	Industria Minera 503	Toluca	MEX	50010	50		Manzanillo,	Cartagena, C	5.18	5.00%	0.259
22	2	L	Diaphram VX	84099192	1.00	EA	CM7	100%	21	4	Nuva Amsterdam 4116 c	Monterrey	MEX	64310	110				10.73	5.00%	0.5365
23	2	M	Piston VX	84099192	1.00	EA	VEN6	72%	14	4	Rua Funchal, 160	São Paulo	BRZ	04551-06	80		Santos, Bra	Manzanillo, I	5.73	3.00%	0.1719
24	2	M	Piston VX	84099192	1.00	EA	VEN7	28%	21	4	Calle Juana Ross 64	Valparaiso	CHL		60		Valparaiso,	Manzanillo, I	1.32	5.00%	0.066
25	1	N	Float VX	84099192	2.00	EA	VEN8	100%	20	4	Av Colombia 4300	Buenos Aires	ARG	1425GMI	35		Buenos Air	Cartagena, C	1.81	2.00%	0.0362

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