**Using Predictive Analytics to Address Risk in Complex Supply Chains**
**By**
**Rachel Marie Schmidt**

B.S. Civil and Environmental Engineering
University of Virginia, 2012

Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering in partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Mechanical Engineering

In conjunction with the Leaders for Global Operations Program at the Massachusetts Institute of Technology

JUNE 2018



Signature of Author ________ Signature redacted ________
Department of Mechanical Engineering, MIT Sloan School of Management
May 11, 2018

Certified by ________ Signature redacted ________
Dr. Maria Yang
Thesis Supervisor, Associate Professor of Mechanical Engineering

Certified by ________ Signature redacted ________
Dr. Charles Fine
Thesis Supervisor, Chrysler Leaders for Global Operations Professor of Management

Certified by ________ Signature redacted
Dr. Roy Welsch
Thesis Supervisor, Eastman Kodak Leaders for Global Operations Professor of Management

Accepted by ________ Signature redacted
Dr. Rohan Abeyaratne
Chair, Mechanical Engineering Graduate Program Committee

Accepted by ________ Signature redacted
Maura Herson
Director of MBA Program MIT Sloan School of Management

**THIS PAGE HAS BEEN INTENTIONALLY LEFT BLANK**

**Using Predictive Analytics to Address Risk in Complex Supply Chains**
**By**
**Rachel Marie Schmidt**

Submitted to the MIT Sloan School of Management and the Department of Mechanical Engineering on May 11, 2018 in partial Fulfillment of the Requirements for the Degrees of Master of Business Administration and Master of Science in Mechanical Engineering.


**Abstract**

Li & Fung (LF) is a global supply chain manager for consumer product brands and retailers. Worldwide, LF contracts with over 13,000 factories. Frequently, these factories experience *incidents*, which are internally defined as "unplanned / unwanted events which have the potential to escalate or have already caused damage to stakeholders within the supply chain." In the factory context, this includes fires, labor strikes, and unauthorized subcontracting events, among others. Every incident costs the factories, LF, and the customers extensive time and resources to mitigate and recover from.

Currently, LF manages incidents as they occur. Moving forward, LF strives to proactively mitigate risk by forecasting the probability that each factory in the supply chain will experience an incident. In addition to avoiding potential factory worker injuries, predicting risk will: (1) save LF time (and money) by being alert to incidents before they occur, (2) protect the LF reputation and maintain trust, and (3) demonstrate how LF is using advanced analytics to build a better supply chain.

This project includes three primary components. First, an assessment to evaluate the impact of incidents on LF was performed, by investigating several case studies of different incident types in different regions of the world. Second, a predictive analytics model to forecast the probability that each factory will have an incident was developed, using historical internal and external data sources. The results are presented quantitatively and visually to provide clear and effective messaging and recommendations to LF management. Insights and challenges are outlined in detail to provide a thorough understanding of the model and recommend future alterations. Finally, the team developed short term and long term action plans to drive responsible sourcing decisions using the available data and initiate industry change.


**Thesis Supervisor:** Dr. Maria Yang
**Title:** Associate Professor of Mechanical Engineering

**Thesis Supervisor:** Dr. Charles Fine
**Title:** Chrysler Leaders for Global Operations Professor of Management

**Thesis Supervisor:** Dr. Roy Welsch
**Title:** Eastman Kodak Leaders for Global Operations Professor of Management

THIS PAGE HAS BEEN INTENTIONALLY LEFT BLANK

**Acknowledgements**

This research represents the culmination of two incredible years at the MIT Leaders for Global Operations (LGO) program. With gratitude and thanks:

*to the LGO Community:*
for the last two years; I could not have imagined the friendships, challenges, failures, successes, learnings, and growth I have experienced alongside you all

*to my advisors - Charlie, Maria, and Roy:*
for your time, support, perspectives, questions, and enthusiasm

*to my LF management team - Pamela, Satte, and Matthew:*
for your guidance, insights, patience, and commitment to your work, communities, and teams

*to my LF colleagues - JP, Wayne, Angel, Chelsea, Vasu, and Dima*:
for teaching me who is who, providing limitless sounding boards, encouraging exploration, and making me laugh every day

*to Brandon:*
for being you

*and to my family:*
for encouraging me to embark on this journey, for inspiring me to dream big, for your unwavering support throughout, and for laughing with me along the way

THIS PAGE HAS BEEN INTENTIONALLY LEFT BLANK

## Table of Contents

# 1. Introduction to Li & Fung and Predictive Analytics

The purpose of this chapter is to introduce the background of Li & Fung Limited (LF) and present the project motivation, problem statement, approach, results, and conclusions.

## 1.1 LF Background

LF is a global supply chain management company for apparel and consumer products brands. Founded in the Chinese city of Guangzhou in 1906, LF began operations as a traditional export company, by trading in porcelain and silk. Through the mid 1900's, LF expanded to trade garments, toys, electronics, and consumer products. In the 1980's, the rise of industrialization in Asia brought new market opportunities and capabilities. LF invested in these opportunities and developed a strong regional presence. The company continued to expand capabilities into sourcing and logistics management through both organic and inorganic growth.[1] Today, LF strives to stay at the cutting edge of global supply chain management.

The Fung Academy provides support across LF. Specifically, the Academy works with business leaders to stay on the leading edge in a rapidly changing world. From leadership development programs to high technology pilot testing to innovative product development; the Academy cultivates a competitive advantage for the organization.[2]

Fung Group employees number approximately 40,000 people worldwide, across 40 countries,[3] and works with 13,000 factories worldwide to provide products to hundreds of customers. LF's business model is designed to contract manufacturing to their extensive factory network on behalf of the customer brands, which are primarily composed of American and European retailers. LF's offerings including assisting the brands with product design, providing material sourcing services, and ensuring high quality products. LF also establishes production plans and schedules, manages shipping logistics, and negotiates with factories on behalf of the customers. LF makes revenue in

---

[1] (Fung Group, 2018)
[2] (Fung Academy, 2018)
[3] (Fung Group, 2018)

a variety of ways, including functioning as a direct supplier, making an agency commission, or selling other specialized services.[4]

## 1.2 Industry Background

On April 24, 2013, an eight-story commercial building located in Bangladesh collapsed. The Rana Plaza incident killed an estimated 1,134 people and injured approximately 2,500 others. It is considered the deadliest garment-factory accident in history, and the world's worst industrial accident in 30 years. The building was occupied by garment factories employing approximately 5,000 people total, a financial institution, apartments, and other selling establishments. Although the retail spaces on the lower floors closed immediately after structural cracks were found in the building, the building ownership team ignored warnings. Garment factory employees were ordered to return to work and threatened with suspended pay for those who refused to come to work. The building collapsed during the busy morning arrival shift. Only the ground floor remained intact.[5]

Locally, thousands of people protested for safer working conditions and for punishment for the ownership of Rana Plaza. The protestors demanded back pay and insisted on a minimum wage of $100 USD per month.

Internationally, the event attracted the attention of politicians, religious leaders, advocacy groups, academia, consumers, and the fashion industry. The collapse and ensuing media coverage shed light on the factory conditions and wages earned to the international community. Protestors in the US and Europe gathered at the storefronts of brands known to have manufactured at Rana Plaza and in greater Bangladesh. The fashion industry responded by creating two major private initiatives: the Bangladesh Accord on Fire and Building Safety ("Accord") and the Alliance for Bangladesh Worker Safety ("Alliance.") These two programs represent first-time partnerships between the some of the world's largest clothing companies to address industry weaknesses and

---

[4] (Mar, 2017)
[5] (Labowitz & Baumann-Pauly, 2014)

risk. Critical evaluations show that the programs are fundamentally the same and are focused on the rapid inspection of Bangladeshi factories and maintaining direct relationships with the brands who fund the agendas.[6]

The Center for Business and Human Rights at the NYU Stern School of Business published a report in April 2014 titled "Business as Usual is Not an Option: Supply Chains and Sourcing after Rana Plaza." The Center has established itself as an authority in the human rights industry in developing ideas that transform challenges and opportunities to "demonstrate that profit and principle can co-exist".[7] The report was developed through vigorous on-the-ground research by reputable experts and asserts the following conclusions about the changing garment industry:

1. **Brands drive pressures down to suppliers to meet consumers' demand for 'fast fashion':** Brands are working to meet consumers' demand for *fast fashion*, or "high volumes of very low-cost clothing sold in up to 12 'collections' per year." To do this, brands reduce the prices paid by consumers and decrease lead times allowed for suppliers. Suppliers can respond to pressure by improving efficiency and/or cutting costs. Often, cutting costs is easier, simpler, and doesn't require initial capital investment. Therefore, typically wages are cut, or work is subcontracted to cheaper facilities.

2. **The riskiest factories are not identified as targets to improve:** Accord and Alliance often have overlapping policies with regards to factory monitoring and training. Together, the programs encompass less than 2,000 of the estimated 5,000 to 6,000 garment factories in Bangladesh. This means the poorest conditions are likely in the unmonitored factories which fall outside of the scope of these programs.

3. **There is increased risk of unauthorized subcontracting:** Indirect, unregulated sourcing has become widely common due to the nature of a supply chain relentlessly pursuing the lowest possible costs. Garment factory owners seek to raise margins and increase capacity, while keeping costs low. This results in poor working conditions, frequent unpaid

[6] (Greenhouse & Harris, 2014)
[7] Stern: Business as Usual is Not an Option: Supply Chains and Sourcing after Rana Plaza

overtime, and low base wages. Indirect sourcing increases risk for factories by reducing control and transparency. It is also increases the risk for brands as quality is not monitored well, production schedules vary, and the probability of human rights violations increases.

4. **The risk of critical infrastructure failure is growing:** Critical infrastructure in factories is poorly maintained. Specifically, unstable electrical supply leads to an increased risk of future factory fires. Following the Rana Plaza incident, funds were funneled to Bangladesh to improve conditions. However, due to increased local corruption, organizations are wary to maintain the support required to drive change in the textile industry.

Although the Stern report is specific to conditions and the state of the industry in Bangladesh, LF encounters components of these challenges across its supply chain. This paper will provide an approach to better forecast and manage these challenges.

## 1.3 Problem Statement

LF works with approximately 13,000 factories worldwide. These are primarily garment factories, which are inherently very labor intense. Factory sizes range, however, it is typical to find a garment factory with hundreds of workers sitting shoulder to shoulder for rows upon rows of sewing machines. Each worker has a specific task, such as sewing the tag onto the garment or hemming the bottom of the item. Some tasks require additional equipment, such as cutting or washing, which may include dozens of machines, typically operated by hand. In many of the countries in which these factories are located, labor is cheaper than automated machinery, meaning the processes remain very labor intensive.

Added pressure by western brands to stay cost competitive in the market filters down to the factory level. Suppliers are squeezed to make more product at lower prices. This can lead to risky work practices such as overworked employees, equipment accidents, delayed electrical safety, or unauthorized subcontracting due to a desire for more work but a lack of sufficient planning.[8]

---

[8] (J.C., 2012)

Across suppliers, LF experiences over 100 incidents per year, which may arise due to unforeseen circumstances. An incident is defined as an "unplanned / unwanted event which has the potential to escalate or has already caused damage to stakeholders within the supply chain." In the factory context, incidents include events such as fire, labor strike, illness, structural damage, or site closure, among others. Incidents may take weeks to resolve, which may cost LF, the supplier, and the brand valuable resources. [9]

Currently, incidents within LF's supply chain are managed as they occur. Internal incident investigators are assigned to each incident to help the factory mitigate the effects, communicate with stakeholders, document the event, recommend a path forward, and provide follow up as needed. In the future, LF hopes to manage incidents proactively, by forecasting the risk associated with each factory in the supply chain. Predicting risk provides LF with the following tangible benefits:

1. Save time: Incident management requires time spent by the LF Vendor Compliance and Sustainability (VCS) team, business units, quality management teams, and customer communications teams, among others. Every hour spent on incident mitigation represents an opportunity cost which could be spent adding value to the business in other ways. In saving time by predicting and mitigating incidents before they occur, the organization inherently saves money.

2. Protect reputation: Highly visible factory incidents can dramatically impact the reputation of the brand, LF, or the factory. Low visibility incidents may also impact the LF reputation, either through reduced product quality, shipment delays, or phone calls from the LF team informing the customer of an injury, fatality, or other violation. By predicting which factories are high risk, LF can take action to help mitigate risk and/or avoid future association with incident-prone facilities.

[9] (Vendor Compliance and Sustainability (VCS) Team, 2017)

3. Leverage big data to drive decision making: LF can use this predictive capability as a competitive advantage for customers and suppliers. This investment in predictive analytics shows LF's applied and tangible commitment to making data driven decisions and building a more robust supply chain.

Historical data serves as the primary input for predicting risk. By evaluating the records of what LF and the industry have experienced historically, the team can determine the principal drivers influencing these events. Through identifying those metrics in current data, the team can forecast the probability that an event will occur based on the relative correlations between the significant metrics and the historical probability of an incident. Therefore, accurately predicting risk is heavily dependent on historical data. Specifically, the data must be:

1. Comprehensive: There must be a broad range of data types to pull from. For example, to predict risk at a factory site, both internal and external data sources need to be considered. Internal data includes metrics that LF collects such as the total number of workers per site, factory audit rating, and quality performance results. External data includes quantitative values for metrics at the country level such as inflation rate, export balance, and a normalized index quantifying women's and girl's rights.

2. Sizable: To develop an accurate estimate of the probability of incident at a factory, there must be sufficient data to confidently understand the historical trends, develop a significant correlation, and project the future result. As the LF incident database grows, the model's accuracy will improve.

3. Accurate: If the internal or external input data is inaccurate, the model will be inaccurate, leading to invalid incident projections.

LF works hard to maintain productive relationships with the suppliers. Due to the nature of the contracting arrangements between suppliers and LF, the suppliers are not *legally* required (although they may be contractually required) to provide LF with data. If a factory does not provide data, LF has limited tools at its disposal to ensure data is delivered. Factory data of interest may include profitability, production plans, schedules, operational efficiency, safety metrics, employment numbers, or customers, among others. In addition to not being legally *obligated* to provide data, there are minimal effective incentives in place to *encourage* data sharing. Oftentimes, suppliers explicitly avoid sharing data with LF due to the fear that LF may use the data against for them. For example, if a supplier informs LF that they experienced a factory fire which stopped production, LF could take action against the factory such as downgrading their audit rating, reducing the volume of orders, or terminating the relationship. This lack of incentives causes significant risk to predictive modeling, as it naturally inhibits open data sharing between the suppliers and LF.

## 1.4 Project Approach

The project aims to develop a simple predictive model to guide LF in managing and mitigating supply chain risk.

The first step is to evaluate the impact incurred by LF as the result of a factory incident. Using internal LF data, the team identifies (a) the three countries with the highest number of incidents and (b) the three incident types which LF either experiences most or is most concerned about. The next step is to perform a case study analysis of three "typical" incident events from within the options identified above. A "typical" incident is one in which the descriptive data falls along the mean with regards to factory size, incident type, impact to the supply chain, impact to employees, etc. A 'typical' incident was chosen for the case studies to avoid skewing the results of the evaluation, since the severity of an incident can vary greatly (from a factory collapse to a minor equipment injury). By using 'typical' incidents, the team develops an understanding of the *average* impact value, both financially and by hours spent by LF team members to mitigate.

Next, a predictive model is developed in the statistical software 'R.' This model requires internal and external data as inputs. Internal input data includes factory specific data such as the number of past shipments to LF, type and number of past incidents, quality performance information, number of workers, etc. External metrics are primarily composed of country level indices from the Economist Intelligence Unit (EIU), a business within The Economist Group that provides relative country, risk, and industry analyses worldwide.[10] Using historical incident data, the model is trained using 70% of the original data set (the training set). That model is then run on the validation data set (30% of the remaining data), to evaluate accuracy. The model is iterated on to improve accuracy. The output of the model is the probability of incident for each factory. In addition to the model output, a simple calculation converts the probability of risk to a financial value. This value assists in raising internal awareness to encourage and incentivize LF leadership to take action. Finally, the model is tested following the researcher's departure on the new incoming data over a period of months.

Finally, an action plan is available to guide the VCS team and LF business units in how to best manage the identified risky factories. This plan focuses on actively engaging with factory ownership and management to identify root causes of the risk and develop plans to mitigate the risk. This action plan will be implemented by the LF team and will be updated as necessary to provide future successful interactions with risky suppliers.

## 1.5 Literature Review

The industry widely recognizes that supply chain disruptions must be proactively managed to avoid painful delays and consequences. As described in this section, historically, companies have managed against disruptions by maintaining large inventories. However, there are costly impacts to this practice. Instead, disruptions can be managed by determining which suppliers are riskiest and working directly with them to improve their risk profile.

In support of the discussion regarding increasingly competitive business environments, supply chain experts Giunipero and Eltantawy assert that traditionally, supply managers have focused on protecting their supply chain from uncertainty, which resulted in typically high inventory and therefore in sub-optimal operational performance. They recommend to instead concentrate on risk management, which can more effectively handle uncertainty through identifying potential losses.[11]

---

[10] (The Economist Group, 2018)
[11] (Giunipero & Eltantawy, 2004)

MIT Sloan School of Management Professors Chopra and Sodhi add to this analysis by explaining that large companies buffer against this risk by holding hefty reserves. However, this practice inevitably drives up costs and hurts profits. To overcome this challenge, Chopra recommends a similar approach to that taken in this thesis which includes testing followed by a tailored mitigation approach.[12] Testing can include various methods used to identify insights into the data and challenges a factory may be experiencing. This may include pilot testing a new technology, developing a detailed survey for users across functions to fill out, or evaluating the changes created following a training program. Following this analysis and the insights determined, a customized strategy can be developed to help the factories or companies identify their root causes and create solutions. This is the same approach taken by this thesis.

Within the above argument to focus on and improve risk management, questions are raised regarding how to *quantitatively* measure management quality. If this can be done effectively, management quality may be tested as a proxy for system productivity. Economics professor and operations expert Van Reenan and colleagues developed a thorough "interview-based evaluation tool that defines scores from one ("worst practice") to five ("best practice") across 18 key management practices." The evaluation focuses on three primary topics: monitoring, targets, and incentives / people management. The interviews are completed by graduate-level professionals with extensive training and preparation, resulting in a total approximate cost of $400 per 45-minute interview. The primary drawback of this evaluation is that strategic decisions (i.e. innovation, pricing, market entry, and leadership among others) made by the management team are not evaluated. The research team tracked baseline data and performed control tests to measure the change in productivity against the changing management survey scores. The team concludes that management quality can be quantitively measured, within bounds.[13]

LF hopes to improve operational efficiency through a proactive risk approach, as opposed to traditionally sacrificing operational performance to achieve protection against supply chain disruptions such as incidents.

---

[12] (Chopra & Sodhi, 2004; Chopra & Sodhi, 2004)
[13] (Bloom, Lemos, Sadun, Scur, & Van Reenan, 2014)

Using predictive analytics to drive decision making and increase confidence is gaining momentum within the textile supply chain industry. Operations experts at DePaul University and the University of Texas leveraged a predictive logistic model to forecast the probability that factory workers in China would leave their current jobs. This analysis was completed in response to concerns that high factory turnover rates were impacting cost, operations, and reputation of Chinese based manufacturing companies. This model successfully identified several significant metrics which are correlated to the probability of employees leaving their current employment position. [14]

Finally, an analysis by leading operations Professors Wu, Blackhurst, and O'Grady evaluates the bullwhip effect as it relates to supply chain disruptions. The problem statement explains, "supply chain networks are vulnerable to disruptions... and failure at any point in the supply chain has the potential to cause the entire network to fail."[15] This statement highlights the severity of the risk and the importance of addressing these incidents through a data driven approach to make the supply chain more robust against failure.

## 1.6 Summary

As the industry faces new pressures from consumers, factories are squeezed to produce more at lower costs. This leads to increased risk in the factory environment, which creates supply chain disruptions, puts individuals in danger, and costs time and money for all stakeholders. This thesis will leverage historical data to develop a simple predictive model to forecast which factories will experience incidents. With this information, LF can proactively work with these factories to reduce their risk.

[14] (Jiang, Baker, & Frazier, 2009)
[15] (Wu, Blackhurst, & O'Grady, 2007)

# 2. Impact Assessment

The first objective of the research is to understand the cost (financial and time-spent) incurred by LF as the result of a factory incident. These values are inherently difficult to quantify because it is primarily composed of time spent managing and mitigating the incident by various members of the LF team. However, the opportunity cost of the time spent mitigating incidents is high and could be reduced dramatically by forecasting and identifying high risk factories.

## 2.1 Data Inputs

In 2016, the LF supplier network experienced over 100 incidents. Each incident costs LF time, money, the potential loss of trust with customers, and possible reputation damage in the industry.

As described previously, this evaluation is highly dependent on accurate incident data from the suppliers. While the suppliers are contractually required to share incident information as soon as possible, they frequently fail to do so due to the fear that they will be penalized for a violation. As a result, LF receives information on incidents through a variety of disparate sources: the media, local nonprofit organizations, onsite LF employees, disgruntled factory employees, or factory management. The inconsistency in receiving reliable information results in incomplete records, inaccurate data, and challenges while working with factories to transparently identify root causes and develop mitigation plans.

To complete the impact assessment, the historical LF incident data was analyzed. Figure 1 below shares the incident types, and the percentage of each type experienced across the supply chain.

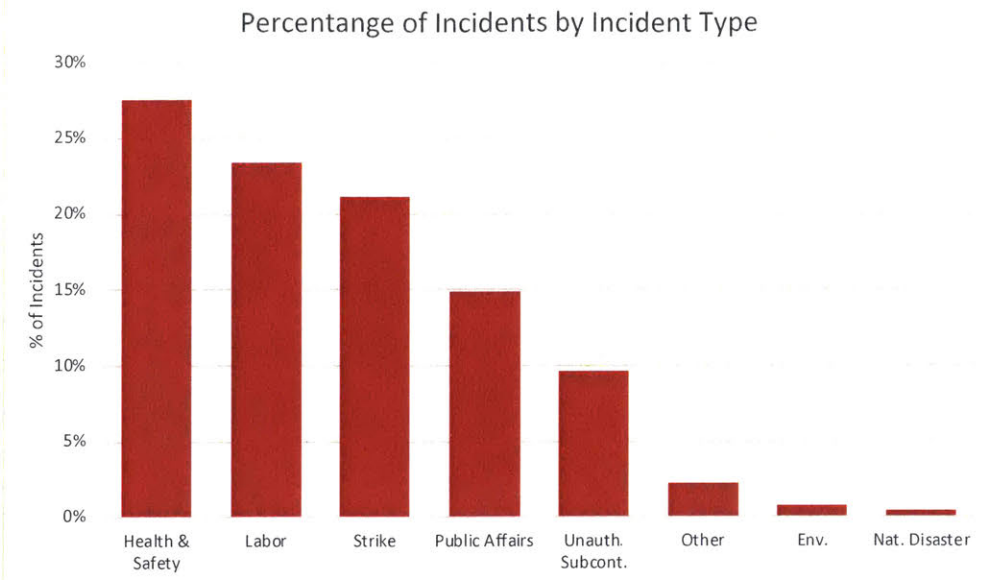


Figure 1: Percentage of incident type across the LF supply chain (~Aug 2015 to Oct 2017)

The data was also parsed to compare the frequency of incidents for each country in the supply chain. Figure 2 illustrates the breakdown by country.

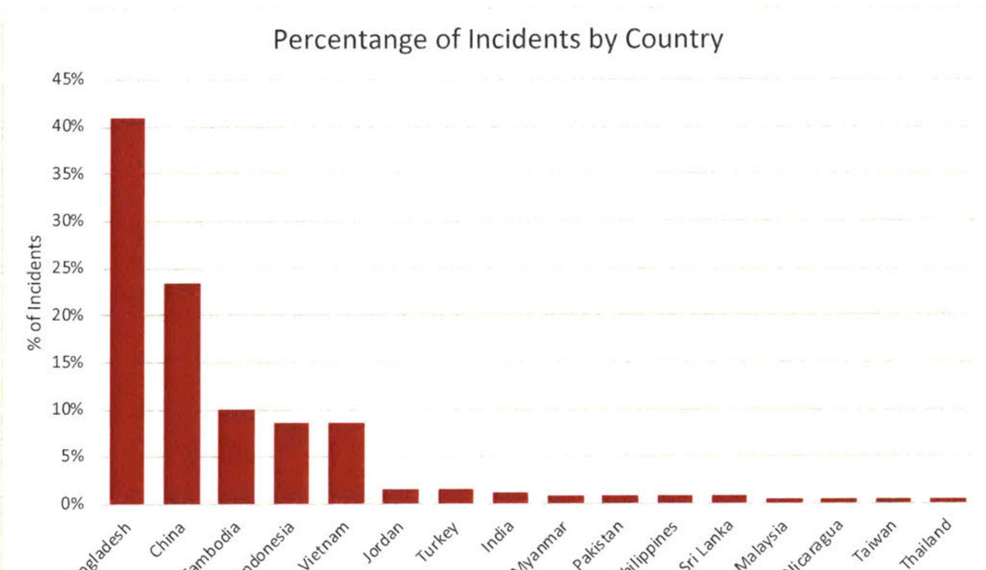


Figure 2: Percentage of incidents by country across the LF supply chain (~Aug 2015 to Oct 2017)

To accurately understand the data conveyed in Figure 2, it is critical to understand the volume of LF work as distributed between these countries. If the volume of work roughly followed the percentages outlined in Figure 2, this distribution of incident frequency would be expected.

Figure 3 shows the percentage of incidents which occurred in each country (same as Figure 2) and compares it to the approximate annual percentage of LF work completed in each country. Figure 3 shows the disparity between the frequency of incidents and amount of work completed. For example, Bangladesh experiences ~40% of the incidents while completing ~3% of LF's annual work. In comparison, China is responsible for ~23% of incidents and ~76% of the work completed.

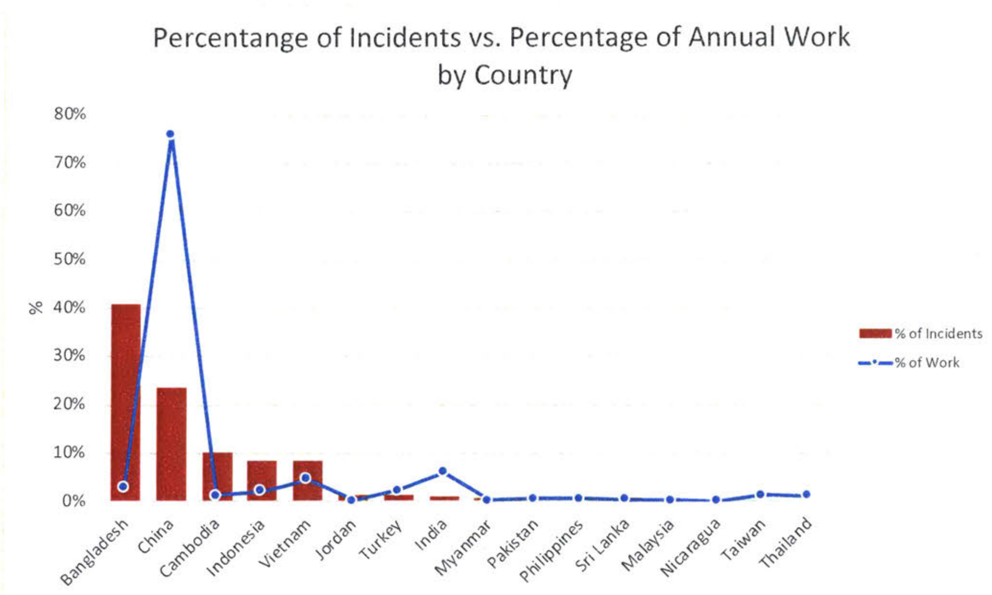


Figure 3: Percentage of incidents by country as compared to the approximate annual percentage of work completed in that country (~Aug 2015 to Oct 2017)

Using the data provided above and through discussions with management, the team determined that labor incidents, factory fires (within the health & safety category) and unauthorized subcontracting would be the focus for the three case studies. Bangladesh, China and Cambodia, the countries experiencing the most incidents, would be the countries evaluated. The following sections introduce the case studies evaluate the results. Please note that some details of these incidents are confidential and therefore are not shared.

## 2.2 Case Study 1: Labor Strike in Bangladesh

The first case study is a labor strike which occurred at a factory in Bangladesh. At this factory, the workers' allegiances were divided across several union factions, as is common in Bangladesh.

On the morning of the incident, two union factions engaged in a physical fight in which five workers were injured and factory machinery was damaged. Work at the facility was stopped for one week. Table 1 summarizes the data from the incident.

**Table 1: Bangladesh Labor Strike Incident Summary**

| Metric | Rating |
|---|---|
| Factory Audit Rating (A = good, F = bad) | C |
| Longevity of relationship with LF | 4 months |
| LF Customer(s) | 1 US-based |
| Downtime caused by Incident | 57.5 hours |
| Previous Incidents | None recorded by LF |
| Number of Employees | ~7800 |

Two weeks after the incident, LF incident investigators arrived onsite to evaluate. Shortly after the investigation, the factory terminated employment for 92 workers. LF worked with factory management to confirm that final payments to these employees were completed. Over two months later, these employees had not been paid, meaning the incident remained "open" (under active investigation). This requires the LF incident management team to regularly follow up with factory management to mitigate fallout, resulting in many hours spent. Overall, the incident investigation cost LF over 80 labor hours, which could have been used for higher value impact to LF. Finally, LF had over $200,000 of product in the facility at the time of incident, which was placed at risk of delay, damage, or loss during this time period.

## 2.3 Case Study 2: Factory Fire in China

The second case study is a factory in a Chinese factory. The fire was caused by heated oil leaking from the facility power plant. The fire was reported by a member of the LF audit team who was coincidentally onsite that day. The incident records state that the LF employee asked about the smoke she saw several times before being asked to evacuate the building. Table 2 lists the additional facts from the factory and incident.

**Table 2: China Factory Fire Incident Summary**

| Metric | Rating |
|---|---|
| Factory Audit Rating (A = good, F = bad) | Not required for unknown reasons |
| Longevity of relationship with LF | 6 months |
| LF Customer(s) | 2 US-based |
| Downtime caused by Incident | 16 hours |
| Previous Incidents | None recorded by LF |
| Number of Employees | ~2000 |

LF had one customer order which was impacted by the incident, so LF informed the affected customer immediately. The factory closed for one and a half days to confirm that the oil leak had been sealed. For the next two months, the LF team conducted an investigation and provided fire safety training to the factory staff. The investigation was closed 68 days after the incident occurred. This incident cost LF approximately 45 labor hours to mitigate and resolve. This time includes the investigation, internal management reviews, customer communications, order adjustments, etc. In addition to the impacted order, over $400,000 worth of LF customer product was at risk of being impacted as a result of this incident.

## 2.4 Case Study 3: Unauthorized Subcontracting in Cambodia

The final incident evaluated is an unauthorized subcontracting event in Cambodia. Unauthorized subcontracting occurs when a primary factory (under contract with LF) contracts with a secondary factory to deliver a portion of LF's order, unbeknownst to LF. The factories benefit because they both receive work and payment (directly or indirectly). Conversely, if the primary factory informed LF that they could not meet the order requirements due to their limited in-house capacity, the entire order may have been moved to another factory. Therefore, the factory is motivated to keep the work, but find a partner to help deliver the product.

Unauthorized subcontracting creates problems because LF has extremely limited visibility into the compliance and safety conditions of the unauthorized facility. If the unauthorized facility had an incident, this could lead to delayed, damaged, or lost product, employee injuries or reputational risk. Often, the unauthorized facilities work on even tighter margins than the primary facility. While it is unproven that these secondary facilities achieve lower marks on compliance, health, and safety, it is hypothesized that conditions are worse in unauthorized factory environments. Finally, it is easy for factory management between the two facilities to collude to ensure that LF does not discover the unauthorized subcontracting practices. This makes it difficult for LF to identify and penalize. Unauthorized subcontracting is forbidden per the LF contract agreement and is considered a "zero tolerance" type of incident.

At the Cambodian factory which this case study is focused on, the LF compliance team discovered discrepancies in the factory's productivity numbers compared to shipped item values. This served as sufficient proof to report an unauthorized subcontracting offense, and the factory was suspended from working with LF for six months. Additional facts on the incident are defined in Table 3.

**Table 3: Cambodia Unauthorized Subcontracting Incident Summary**

| Metric | Rating |
| --- | --- |
| Factory Audit Rating (A = good, F = bad) | C, changed to F following this incident |
| Longevity of relationship with LF | 19 months |
| LF Customer(s) | 1 UK-based |
| Downtime caused by Incident | None; but LF stopped working with this factory |
| Previous Incidents | Suspected of unauthorized subcontracting twice before; no proof available previously |
| Number of Employees | ~1400 |

LF informed the affected customer of the unauthorized subcontracting offense two days after the discovering the data discrepancies. LF formally investigated the incident 11 days after the discovery, and the factory audit rating was changed from a "C" to an "F".

This factory produced highly technical outdoor gear for their customers. At the time of this writing, the LF team had been searching for a new supplier for over four months. This means the customer's orders were not filled for four months, likely resulting in limited production, frustration over profit loss, and a lack of trust with LF. Additionally, this incident has cost LF over 180 labor hours in costs to mitigate and seek out new suppliers.

## 2.5 Impact to Suppliers and Customers

Through this evaluation, the primary focus was in quantifying the costs incurred by LF, as opposed to quantifying the costs incurred by the factory or customer. However, the impacts to factories and customers were evaluated qualitatively. Overwhelmingly, factories bear the brunt of the cost incurred by an incident, as they pay for direct costs such as structural damage, medical bills, rush shipping, lost wages, or sustained fines, among other expenses. Additionally, the suppliers suffer indirectly when the factory is shut down due to lost productive time. For example, during a work stoppage, the supplier cannot actively fill orders, causing them to fall behind on production, and requiring them to pay back-wages during shutdown periods. Production delays may be made up for by forcing employees to work overtime for limited pay, which results in an unhappy workforce, decreased product quality, and higher operational costs. Finally, insurance premiums may rise as the result of an incident. These problems can continue to compound on themselves to drive worse conditions in the factory.

Depending on the scale of the incident and the recovery measures implemented by the factory, the customer may or may not be impacted. Frequently, the factory and LF can work together to reduce the impact on the customer, either by working *paid* overtime, rush shipping the order, or implementing other short-term fixes. However, occasionally the impact to the customer can be significant. For example, in the third case study presented above, the supplier was terminated from working with LF due to unauthorized subcontracting. Unfortunately, that supplier manufactured very technical outdoor gear for a large LF client. The LF team had to search for a new supplier for several months, resulting in significant profit loss for the customer.

## 2.6 Results

The three case studies evaluated above were used to develop a quantitative understanding of the total impact created by incidents within LF's supply chain. The primary takeaways from this evaluation include:

- **Hours:** Annually, factory incidents demand over 12,000 hours of LF labor time to mitigate the effects. The opportunity cost of this time is very high. The individuals involved in incident mitigation processes could be spending time adding value to LF, through activities such as improving operations, developing new business, or growing innovative practices.

- **Impacted Shipments:** Over $200M USD of product is at risk of being delayed, damaged, or lost annually. Depending on the type of incident, resulting delay, and customer agreement, these incidents could significantly negatively impact the future business relationship between the customer and LF, potentially decreasing business or terminating the relationship.
- **Productivity:** Incidents decrease factory productivity. By stopping work to manage an incident, factories lose valuable time in which to manufacture orders and attract new clientele. Depending on the incident, they will have to backpay their workers for lost production time, which further decreases factory efficiency and profitability.
- **Reputation:** Depending on the type, scale, delay, and publicity caused by an incident, the reputation of the supplier, LF, and/or the customer can be severely damaged. Reputation damage in the age of digital information and socially aware consumers can have a significant impact on future sales and brand perception.

This evaluation was focused on three types of incidents across three countries, to summarize the average risk for the supply chain. In the future, a more systematic assessment could be valuable to comprehensively understand the baseline risk. It is important to note that *every* factory in the supply chain poses a risk. This thesis asserts that predictive analytics can forecast incidents, which will provide LF will the tools needed to build a more robust and data-oriented supply chain, primarily through working directly with high risk factories to reduce their risk of incident.

## 2.6 Summary

On average, factory incidents cost LF over 12,000 labor hours in annual mitigation activities; time which could be spent on higher value activities. Additionally, over $200M USD of customer product is at risk of being delayed, damaged, or lost annually, due to incidents in the supply chain. This impact assessment provides a quantitative understanding of the impact and costs incurred by LF as a result of incidents in the supply chain.

# 3. Predictive Model

The second objective of this research is to build a predictive model to forecast the probabilities that each factory will experience an incident. Predictive models are composed of independent variables (metrics which may or may not be correlated with one another) and (in this case) one dependent variable. In this model, the dependent variable is the probability of incident. This section describes the data inputs, explains the data exploration process, outlines the statistical methodology employed, and identifies the challenges encountered.

## 3.1 Model Objectives

The primary objective of this predictive model is to provide a quantitative understanding of the risk inherent at each factory within the supply chain, given the available data. The secondary objectives are to (1) recognize the statistically significant metrics which correlate to high risk facilities and (2) identify the gaps that exist in the current LF data collection and management systems, such that they can be improved upon.

## 3.2 External Data Inputs

External data was either purchased by LF from the EIU or is publicly available. The EIU is a business unit within The Economist Group which analyzes country and industry data to provide forecasting estimates and insights. These quantitative metrics are normalized on a scale from 0 to 100, where a risk of "0" means that there is essentially no risk, and a ranking of "100" means that the country is highly at risk of the metric. The first data set was received by LF on November 1, 2017 and additional datasets will be provided to LF every subsequent quarter. Additional country level data was gathered from the World Bank's publicly available records. Definitions for each country level, external, metric and the hypothesis for how the metric impacts incident occurrence are listed below.[16] Additional information, including details and definitions for the sub-metrics included within each metric are listed in Appendix 1.

---

[16] (Economist Intelligence Unit, 2017)

- Overall Assessment [EIU]: This value represents the overall score from the EIU assessment and is calculated as an average of the 84-itemized metrics. As this metric represents an average of the country risk, this may provide a strong correlation to the probability of incident.

- Financial Risk [EIU]: This risk aggregates the EIU financial risk metrics including devaluation risk, depth of financing, access to local markets, marketable debt, banking sector health, and stock market liquidity. This risk may provide insights into the flexibility and security of the financial system, creating a correlation for the stability in the country.

- Foreign Trade and Payments Risk [EIU]: As defined by EIU, this risk answers the question, "What are the risks in getting inputs/money into or out of country?" This risk may be valuable within the model, as it may summarize the relationship between the country and relationships with foreign partners.

- Infrastructure Risk [EIU]: As defined by EIU, this risk answers the question, "What is the risk that infrastructure deficiencies may cause a loss of income?" This risk may provide a correlation to risk given the state of the country's infrastructure and an understanding of government support, priorities, and stability.

- Labor Market Risk [EIU]: As defined by EIU, this risk answers the question, "Are labor market factors likely to disrupt business operations?" This risk may provide insights into child labor, forced labor, women in the workforce, and other labor opportunities and challenges in the country.

- Legal and Regulatory Risk [EIU]: As defined by EIU, this risk answers the question, "is the legal system likely to safeguard investment?" This risk may serve as a comparable metric to the stability of the country's judicial system, the competency of the legal system, and the support behind regulatory frameworks.

- Macroeconomic Risk [EIU]: As defined by EIU, this risk answers the question, "Is the economy stable and predictable?" Macroeconomic risk provides insights into the stability of the country's economy, potential future economic policy, and the stability of the metropolitan areas and the citizens.

- Political Efficacy Risk [EIU]: As defined by EIU, this risk answers the question, "Does the political culture foster the ability of business to operate effectively?" This risk relates to the impact of ongoing politics on businesses with regards to funding, policy, and the level of flexibility the business sector experiences.

- Political Stability Risk [EIU]: As defined by EIU, this risk answers the question, "Are political institutions sufficiently stable?" This risk clarifies the stability of the political system, and therefore the consistency of the country's regulations, leadership, and expectations.

- Security Risk [EIU]: As defined by EIU, this risk answers the question, "Is the physical environment sufficiently secure?" This risk directly correlates to the physical safety felt by the population in the country.

- Tax Policy Risk [EIU]: As defined by EIU, this risk answers the question, "Are taxes low, predictable and transparent?" Tax policy provides insight into the government system, availability of public funds, and expectations for those funds.

- Youth Population [World Bank]: This metric states the proportion of the population that is below age 14, by country. LF has listed child labor and forced labor as zero tolerance offences. As a result, LF closely monitors factories which they suspect of using these labor tactics. Understanding the distribution of distinct populations may correlate with the riskiness of the country.

- Inflation Rate [World Bank]: The inflation rate of a country is a direct indicator of their economic performance. Countries with higher inflation rates may be steadily growing or may be experiencing a temporary positive upswing in the economy. This indicates trends such as job opportunity and growth in the country; which may decrease overall risk as citizens experience increased stability.

- Export Partner Share [World Bank]: This metric represents the proportion of the global export trade shared by each country in the year 2016. This percentage is calculated by taking the value of annual exports for one country (USD) and dividing by the total global export value (USD) for the same year. This metric may provide an indication of where the country stands as compared to its regional neighbors and with regards to the global economy.

These 14 metrics represent the external data inputs into the predictive model. The following section will describe the internal variables, or the data collected on each factory by LF.

### 3.3 Internal Data Inputs

Many of the LF functional groups have unique databases which collect data that is specific to that function, for instance, compliance data or quality data. However, much of this data has not yet been evaluated in conjunction with other internal LF data. This predictive model aggregates these data sources. Specifically, this analysis includes four of LF's primary databases, which are each outlined below. Within each database description, the variables tested in the various model iterations are briefly described. Note that not all of the variables listed are used in the final version of the predictive model, instead, only those variables which are proven to show statistical significance (i.e. proven correlation with the probability of incident) are included in the final model.

1. **"XTS" database:** is the largest LF database and is used across the LF functions and business units. The XTS database variables include:

   - Factory Location: This field captures which country the factory is located in and may provide more detailed information such as the city or region.

   - Freight on Board (FOB): FOB is a term used to clarify who (the seller or the buyer) is responsible for paying for transportation charges and to designate who holds liability for products that may be damaged during shipping.[17, 18] In this context, it represents a close proxy to the total value of LF goods produced at the factory over the past year. For confidentiality reasons, the numerical values of FOB have been replaced by lower bound and upper bound "bands" ranging from one to seven, where a one represents a low FOB and a seven represents high FOB at a factory. Details are provided in Table 4.

**Table 4: FOB Confidentiality Bands**

| Band | FOB Lower Bound (USD) | FOB Upper Bound (USD) |
|---|---|---|
| 1 | $0 | $9,999.99 |
| 2 | $10,000 | $99,999.99 |
| 3 | $100,000 | $999,999.99 |
| 4 | $1,000,000 | $9,999,999.99 |
| 5 | $10,000,000 | $99,999,999.99 |
| 6 | $100,000,000 | $999,999,999.99 |
| 7 | $1,000,000,000 | $9,999,999,999.99 |

- Quantity: The quantity recorded for each factory represents the average quantity of product that is in process at a supplier at any one time. Similar to FOB, the actual number of products per factory has been masked for confidentiality reasons. Table 5 defines each lower bound and upper bound quantity range.

**Table 5: Quantity Confidentiality Bands**

| Band | Piece Lower Bound (unit) | Piece Upper Bound (unit) |
|---|---|---|
| 1 | 0 | 9,999 |
| 2 | 10,000 | 99,999 |
| 3 | 100,000 | 999,999 |
| 4 | 1,000,000 | 9,999,999 |
| 5 | 10,000,000 | 99,999,999 |
| 6 | 100,000,000 | 999,999,999 |
| 7 | 1,000,000,000 | 9,999,999,999 |
| 8 | 10,000,000,000 | 99,999,999,999 |

- Status: This metric indicates the current standing of the relationship between the supplier and LF. Discrete statuses include: active, processing, dormant, deactivated and inactive.

---

[17] (Hudson, 2017)
[18] (Freight on Board, 2018)

Factory status can be altered as a result of a compliance problem. It can also be altered because the primary customer went out of business, a new technical skillset was required and not achieved, or the factory shut down. As a result, the correlation between factory status and probability of incident is hypothesized to be low.

- Number of Workers: This metric provides the average number of employees working at the supplier. This metric and the underlying implications vary based on the country. Due to the variation in country operations, it is difficult to predict a strong correlation between number of workers and probability of incident. However, the number of employees may provide insight into the factory organizational structure and responsibilities. For example, a factory with 100 employees may not have the capacity to hire a full-time compliance officer. Instead, this responsibility may be split between several managers or may fall informally amongst the leadership team, meaning there is little responsibility for meeting compliance requirements. However, a factory with 5000 workers may have a more structured management team, including a full-time compliance officer watching to prevent and manage incidents appropriately. Therefore, the total number of workers is hypothesized to have a weak, yet possibly correlated relationship with the probability of incident.

- Audit Rating: Each factory in the supply chain is required to undergo regular audits, certified by LF or by a customer whose process has been validated by LF. Ratings are categorized as A, B, C, D, or F, with "A" being the best rating and "F" being the worst. The factors on which the audit rating is determined include primarily compliance related metrics: accountability/transparency and ethics, management systems, environment, labor, and health and safety. Factories are inherently incentivized to aim for higher ratings so that they may be chosen for future orders over another factory which is not rated as highly. Additionally, the time periods between audits differ by rating. An "A" rating requires the factory to be re-audited every 18 months, a "B" rating requires new audits every 12 months, a "C" factory requires audits every nine months, and a "D" factory requires new audits every three months. An "F" factory is ineligible for audit for the next six months and will not receive any orders from LF for six months. Factories are required to pay for every audit conducted. Therefore, factory management saves money by paying for less frequent audits. Due to the compliance-related nature of the audit rating, it is hypothesized that the audit rating will provide a strong correlation to the probability of incident.

- Number of Shipments: The metric indicates the number of shipments which have been sent from this factory to LF over the lifetime of the relationship with LF, or beginning on January 1, 2015, whichever occurred later. This value is used to calculate the dependent variable and therefore is not correlated to the probability of incident.

- Days Since First Order: This metric is a calculation of the number of days since the factory's first shipment to LF. This value indicates the length of the relationship between the factory and LF, which may imply the nature of the relationship (i.e. a long relationship may mean that the factory and LF work well together).

- Item Value: This metric is calculated by dividing the FOB of the factory by the quantity of product at the factory. As a result, this value is highly dependent on those two metrics, meaning that FOB, quantity and item value could not all be tested in the model simultaneously. Instead, it was hypothesized that this variable could aggregate the information from the other two, and possibly provide a more significant correlation.

2. **"MQC" database:** is maintained by each discrete business unit and stores factory specific quality metrics such as defect rate, in order to track performance against customer targets. Per the Executive Vice President of Quality Assurance in the LF Private Label business unit, the two most indicative quality metrics are the first final pass rate and the defect rate, both described below.[19]

    - First Final Pass Rate: This value indicates the average success rate of final inspections per year. Specifically, every shipment undergoes a final inspection. If that shipment is rejected and the order re-tested, it would negatively impact this pass rate. As a reference, the LF

[19] (Miller, 2017)

Private Label business unit has a first final pass rate goal of 95%. It is hypothesized that quality is highly correlated to the probability of incident. If a factory can consistently provide high quality orders, they may have skilled management and/or dedicated workers who may also be committed to avoiding compliance or health and safety issues.

- Defect Rate: This metric measures the proportional number of defective garments over the number of total units produced per year. Shipments are typically spot-checked to measure the quality of an outgoing shipment. The defect rate is calculated from those spot-check reviews. The LF Private Label business unit has a goal to achieve a 2.5% defect rate across factories. It is hypothesized that the defect rate and the first final pass will be correlated with each other, due to the similar strategies required to achieve and measure certain quality metrics. Due to this correlation, it is likely that both metrics will not be significant in the final model, but it is hypothesized that either first final pass rate or defect rate will be strongly correlated with the probability of incident.

3. **Capacity Building database:** includes information for when a factory purchases an LF training program, including how many employees complete the training and the number of training days conducted. The primary metric from the capacity building database includes:

    - Employee Days of Training: This metric was calculated by multiplying the number of days over which training was conducted at the factory by the number of factory employees who participated in the training. This provides a consistent metric over which to compare all factories. Of the 13,000 factories, only 265 factories (~2%) have participated in LF capacity building programs from February 2016 to May 2017. Due to the small sample size of factories participating in this program, is it hypothesized that this metric will not provide a strong correlation to the probability of experiencing an incident.

4. **Incident database:** is managed by the VCS team and collects information to record, track, manage, and mitigate incidents. The incident data used to create this model is partly compiled from the previously-used tracking system, "Safeguard," and from the new "Compliance" platform. Along with the change in data platforms, the incident categories changed during this

research timeline. The previously-used incident categories were deemed to be unclear and contradictory by the VCS team. The updated project categories now include: (a) health and safety, (b) strike, (c) labor issue, (d) public affairs, (e) unauthorized subcontracting, (f) environmental issue, (g) natural disaster, and (h) other. Appendix 2 includes a table used to distinguish between the category types. Some incidents can be categorized as more than one category, which is then narrowed down to one category based on the specific incident context. The primary metrics from the incident databases include:

- Incident ID: Every incident is assigned an incident ID number to track progress and record data accurately.

- Customers: During an incident, the LF customers that have product at that facility are recorded. Those customers will be contacted if their order is impacted or if the factory has committed a zero-tolerance offense.

- Operating Groups: Many factories work across LF operating groups. When an incident is reported, it is standard practice to determine which operating groups the factory was working with and inform all appropriate LF management teams.

- Severity Level: Each incident is assigned a subjective low/medium/high severity level immediately after the incident and again when the incident investigation is closed. This metric is intended to capture the details not captured in the incident report, such as the level of violence instigated during a strike. If the incident is rated with a "high" severity, it will be more closely managed by the LF team.

- Number of Incidents of a Certain Type: Different incidents may be the result of different factors within the facility. For example, a high number of labor strikes may be caused by low wages across the country whereas a high number of health and safety incidents may be caused by a broken drinking water quality system at the specific facility. As a result, each type of incident has a separate predictive model. These models will be aggregated to produce one final list of forecasted incident probabilities. The number of incidents of each type, categorized by factory is required to calculate the dependent variable in the model.

- Probability of Incident [dependent variable]: To determine which factors predict risk, it is necessary to have a dependent variable which is the calculated probability of incident. This value is calculated by dividing the number of incidents of a certain category by the number of total shipments of a factory. This calculation assumes that (1) only one incident occurs per shipment and (2) the only incidents recorded are those which occur while an LF shipment is being completed. This probability of incident is the same type that will be forecasted as the output of the model; once the independent variables have been trained on an accurate model.

## 3.4 Logistic Regression

Ultimately, this researcher used a logistic regression algorithm to develop and run this model. This section explains logistic regression and the steps taken to create the model.

### *3.3.1 Governing Equation*

This model uses a logistic regression, which is "a predictive analysis… used to describe data and to explain the relationship between a dependent binary variable and one or more nominal, ordinal, interval, or ratio-level independent variables."[20] This method provides an understanding of the relative importance of the effect each independent variable has on the probability of incident. Logistic regression uses a function bounded within [0,1] to model the *probability* of the dependent variable using the maximum likelihood method. The standard probability function of a logistic regression is presented below in Equation 1, where:[21]

- P = probability of incident
- β = independent variable coefficient
- x = independent variable value

[20] (What is Logistic Regression?, 2018)
[21] (ESD, 2017)

**Equation 1**

$$P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3)}} = \frac{1}{1 + e^{-X_i \beta}}$$

### *3.3.2 Data Cleaning and Imputation*

When performing a regression, the first step is to collect and clean the data.[22] Specifically, to clean the data means to manage missing data points by calculating specific values to substitute in, a process known as imputation.[23] Without imputation, the researcher be forced to either remove rows which include empty cells or replace the empty cells with zeroes; both processes would skew the results.

For this analysis, imputation methods differ slightly based on each variable, although most imputations were calculated using the mean of the observed values for that variable.[24] The imputation methods varied due to the initial level of detail. For example, if detailed information was available, a more robust imputation method was used, to avoid reducing the granularity of the variable. For the external data sources, minimal imputation was required. The EIU provides LF with comprehensive data for all of the countries included in the LF supply chain. The World Bank data (used for youth population, inflation rate, and export partner share) did not include some countries due to lack of reliable data. In these instances, the missing data was imputed by taking the average of the United Nations (UN) Geoscheme region in which the missing country is located. The relevant portions of the UN Geoscheme are listed here:[25]

- Africa: Egypt, Ethiopia, Kenya, Lesotho, Madagascar, Mauritius, Morocco, Swaziland, Tunisia

[22] (Karen, 2018)
[23] (Yuan)
[24] (Karen, Seven Ways to Make up Data: Common Methods to Imputing Missing Data, 2018)
[25] (United Nations, 2017)

- Asia: Bahrain, Bangladesh, Cambodia, China, Hong Kong, India, Indonesia, Israel, Japan, Jordan, Laos, Macau, Malaysia, Myanmar, Pakistan, Philippines, South Korea, Singapore, Sri Lanka, Taiwan, Thailand, Turkey, Turkmenistan, Vietnam
- Europe and North America: Austria, Belgium, Bulgaria, Canada, France, Germany, Italy, Latvia, Luxembourg, Macedonia, Netherlands, Poland, Portugal, Romania, Spain, Ukraine, United Kingdom, United States
- Latin America: Argentina, Brazil, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua

For the internal data variables, imputation methods varied. From the beginning of the analysis, factories without a standard six-letter factory code or a country of origin were removed from the data set. Any remaining missing factory data was imputed by using the average value of the country in which the factory was located. If there was not sufficient country level data, an average across the UN Geoscheme region was used.

### *3.3.3 Data Centering and Scaling*

To accurately compare the data, without complications regarding the scale of different variables, the researcher centered and scaled the data prior to building the model. Centering is completed by calculating the average of a column of data and subtracting that average from the individual data points in the column. Next, scaling is performed on the centered data. Scaling is completed by dividing the individual data points of the centered columns by their standard deviations. Centering and scaling the data allows for accurate comparisons to determine which data is statistically correlated with the probability of incident.[26]

### *3.3.4 Training, Validation, and Test*

To build a logistic model, the data is split into three sets: (1) a training set, (2) a validation set, and (3) a test set. In this case, the training set makes up 70% of the historical data and the validation set makes up the remaining 30% of the historical data. The test set is comprised of data collected

---

[26] (scale, n.d.)

in the future (in this case, data collected from November 2017 to February 2018), to test the results of the final model.

The role of the training data is to "provide the raw material from which the predictive model is generated."[27] Predictive models are built entirely on data from the training sets.

Conversely, the validation data set "is employed to evaluate the performance of the model… [and] provides us with some guidance as to the accuracy we might expect."[28] Essentially, the validation set is designed to *simulate* future data, on which we can evaluate the accuracy of the model. However, because future data is unavailable at the time of model development, we split off some of the historical data to serve this purpose (i.e. create the validation set). This randomly assigned division of data between training and validation sets provide an honest assessment of the performance of the model.

Finally, once the model has been developed and iterated on (by the training set) and confirmed as accurate (by the validation set), it can be tested for ultimate accuracy by data collected in the future; the test set. In the instance of this research, the test set includes data collected from November 2017 through February 2018.

### *3.3.5 Alternate Models*

There are many possible ways to develop statistical forecasts, including various alternative statistical and machine learning methods. This section provides short descriptions of the alternative options considered, and the reasons why those algorithms were not used to create this model. In selecting the appropriate model to use, the researcher relied on one of the secondary goals of this predictive model, which is to understand which metrics are driving the risk profiles. Therefore, the algorithm type selected needs to be transparent enough to provide those insights.

---

[27] (Steinberg, 2014)
[28] (Steinberg, 2014)

- Linear Regression: these models are used to estimate the real values of a variable, based on continuous independent variables. The relationship is established by determining a best fit line amongst the significant variables. [29] This model was not appropriate for this evaluation because the output needed requires a probability as opposed to a calculated, non-bounded value.
- Decision Tree: these models are primarily used for classification problems, as they are structured by defining variables into significant attributes.[30] This type of model wasn't used due to the number of continuous variables included in the datasets and the resultant complexity that this model would produce.
- K – Nearest Neighbors: this algorithm can be used to build many types of models. The algorithm stores significant amounts of data and classifies new data based on the number of nearby "neighbors" within a specified distance. This option is computationally time intensive, so it was not chosen for this predictive model.[31]
- Random Forest: these algorithms require significant computational power as it essentially repeats the decision tree model process several times before identifying a final prediction. The output of this model is a "black box" meaning it is difficult to interpret which factors are statistically significant. This is why this algorithm type was not chosen.[32]
- Neural Network: this deep learning method is a system which is modeled loosely on the human brain. Each data category is a "node" and each node has an assigned "weight." The nodes receive data and feed information forward to the next, more concise layer of nodes. Initially, the weights and relationships are assigned randomly. Through the model, they are iterated until the system determines the optimal output layer. This type of statistical analysis does not provide transparent results and is difficult to explain to users as it is not intuitively understood or explained. For these reasons, this type of model was not used in this predictive model.[33]

---

[29] (Ray, 2017)
[30] (Ray, 2017)
[31] (Ray, 2017)
[32] (Srivastava, 2014)
[33] (Hardesty, 2017)

## 3.4 Results

The results of this predictive logistic model can be evaluated through many potential lenses. This section includes an evaluation of the model accuracy and examples of how the data can be analyzed to best provide the business units with valuable insights. Additionally, this section identifies specific insights that have been discussed in detail with the LF management teams.

### *3.4.1 Model Accuracy*

Given the nature of this logistic regression model, accuracy was measured through the ROC curve and corresponding Area Under the Curve (AUC) value. ROC is a commonly used technique to visualize the performance of a model using a binary classifier (in this case, whether or not an incident occurs). See Figure 4 for the overall ROC curve of the logistic model.

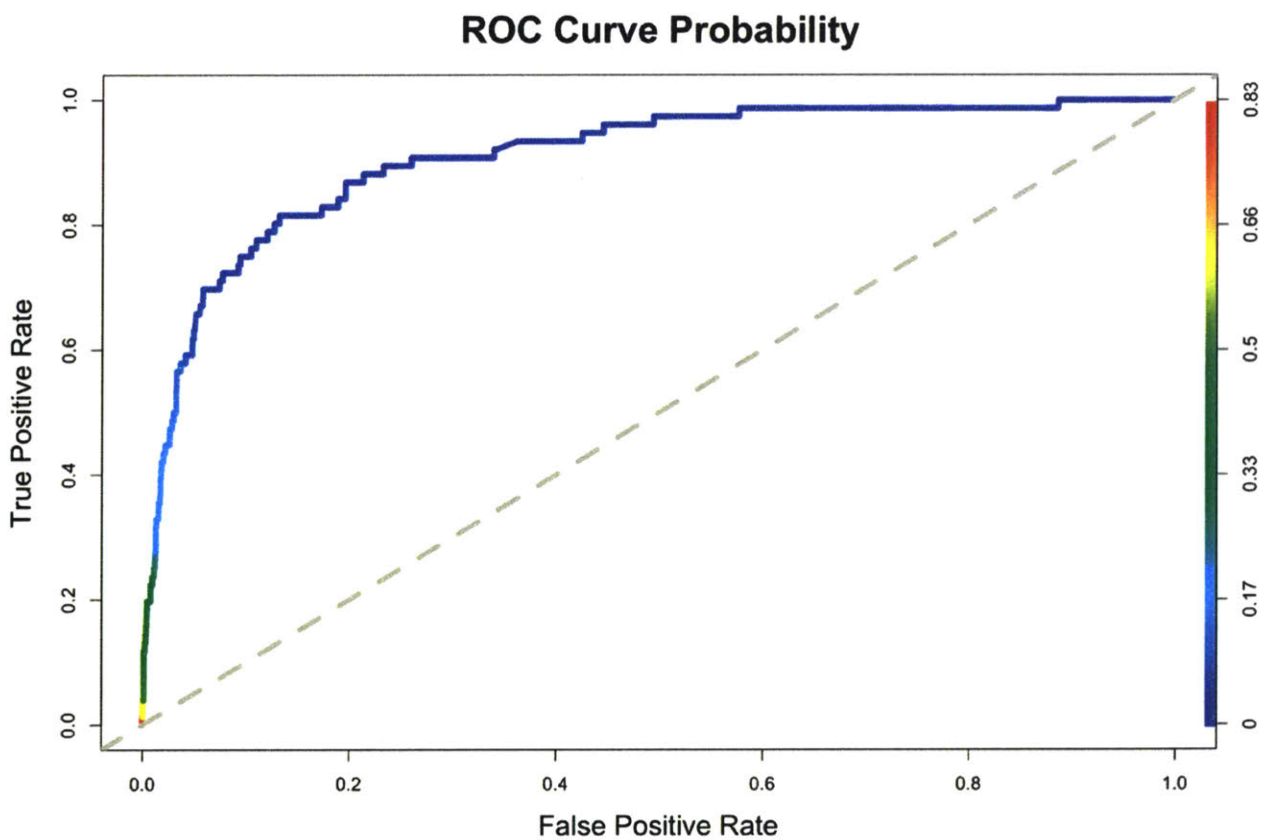


Figure 4: ROC curve visualization. Accuracy is calculated as area under the ROC curve (AUC), which is calculated to be 91% for this model.

The x-axis represents the false positive rate, which is a measure of how often the predicted value is incorrectly positive, given that the actual classification is negative (see Equation 2).

**Equation 2**

$$False\ Positive\ Rate = \frac{False\ positives}{All\ negatives}$$

Similarly, the y-axis represents the true positive rate, which determines how often the classifier predicted positive, given that the actual classification is positive (see Equation 3).

**Equation 3**

$$True\ Positive\ Rate = \frac{True\ positives}{All\ positives}$$

The true positive rate and the false positive rate both range from 0 to 1. The ROC curve can be quantified to understand the performance of a model by calculating the area underneath the ROC curve, or the AUC. Figure 4 shows an AUC of 91%. The gray, diagonal dotted line shown in Figure 4 represents an AUC of 50%, or a performance of 50%. In other words, this line represents a 'guess' as to whether or not a factory will occur at an incident. An AUC of 50% is considered poor, while an AUC of 1 indicates a nearly perfect classifier.[34] Overall, this measurement of accuracy indicates that 91% of the time, the model will accurately predict whether or not the factory will have an incident.

### *3.4.2 Statistical Significance*

Simply stated, statistical significance "helps quantify whether a result is likely due to chance or [due] to some factor of interest," according to Tom Redman, prominent statistical and data analysis author.[35] In this model, a 95% confidence interval is employed, which means that there is a 95% chance that the value produced will fall within the range identified. This corresponds to an alpha value of 0.05 (or 1 – 95%). Therefore, any variable that has a resultant "p-value" of less than 0.05

[34] (Markham, 2014)
[35] (Gallo, 2016)

will be *significant*. The values deemed to be statistically significant in this model are listed in Table 6.

This model used several levels of statistical significance to build a transparent and robust view of the results. A highly significant variable ("High" in Table 6) has a p-value of less than 0.001; a reasonably significant variable ("Med" in Table 6) has a p-value between 0.001 and 0.01; and a significant variable ("Low" in Table 6) has a p-value of between 0.01 and 0.05. When predicting the risk of incident across all incident types and all factories, the factors identified in Table 6 were determined to be statistically significant.

**Table 6: Statistically Significant Factors**

| Metric | Statistical Significance | Data Robustness | Application |
|---|---|---|---|
| Freight on Board (FOB) | High | Low | RISK ↓ as FOB ↓ |
| Legal & Regulatory Risk | High | Low | RISK ↓ as Legal & Regulatory Risk ↓ |
| Export Partner Share | High | Low | RISK ↓ as Export Partner Share ↑ |
| Total # of Workers | Med | Med | RISK ↓ as # Workers converge on 5,000 – 10,000 |
| Political Stability Risk | Med | Low | RISK ↓ as Political Stability Risk ↓ |
| Quality | Low | High | RISK ↓ as Quality ↑ |

Data robustness is a qualitative metric, intended to convey the quality of input data provided for each metric. For example, FOB is rated "Low" data robustness, because the input data was divided into seven lower and upper bound bands ranging from $0 USD total FOB for one year up to $1B USD total FOB. This results in large divisions of coarse data, which could provide inaccurate results. Additionally, Legal & Regulatory Risk and Export Partner Share were ranked with "Low" data robustness because they are country level metrics. This means that in a large country like China there is no change in these metrics with regards to regional differences. Through the discussion of these results, it is critical to remember that (1) the model will improve with improved data accuracy and (2) the model can identify and present *correlations*, not causation.

### *3.4.3 Converting Risk to Financial or Hourly Value*

As discussed, the output of this predictive model is a probability that each factory will experience an incident. In order to effectively present these results to LF business leaders, the data must be further interpreted to show a quantitative value of risk. The team developed two such values that were determined to be the most accurate and relatable risk values:

1. The number of LF labor hours that are at risk of being used to mitigate and manage if an incident were to occur at a factory.
2. The value of FOB that is at risk of being delayed, damaged, or destroyed if an incident were to occur at a factory.

Both of these values were calculated using the impact assessment discussed previously and are visually represented as the area under the risk profile curve.

The impact assessment in Section 2 explains that each incident in the LF supply chain requires approximately 90 hours of LF time to mitigate and manage. Therefore, to calculate the hours at risk due to any one incident, the researcher multiplies the probability of incident by 90 hours. To understand the hours at risk for a specific customer/country/etc., sum all of the at-risk factory hours under the curve, to determine the final impact.

Similarly, the team quantifies the FOB that is at risk for each analysis. As discussed, the FOB data was divided into seven bands. There are no factories that meet the requirement for the highest band ($1B USD to $10B USD), so this FOB range is removed from the evaluation. In the rest of the financial bands, we assume that there are factories spread throughout the range. For example, in FOB range #2, we assume that some factories operate at the low end, near $10,000 USD of FOB, and some operate at the high end, near $100,000 USD. To calculate the approximate FOB at risk for each factory, follow Equation 4 below, where HV stands for "High Value" (or $100,000 in FOB range #2) and LV stands for "Low Value" (or $10,000 in FOB range #2).

**Equation 4**

$$FOB\ at\ Risk = \frac{HV + LV}{2}$$

Similar to the hourly risk, each of the individual factory FOB risk values can be summed to determine the overall impact of incident risk for a collection of factories. Using these two conversion techniques, we can adequately convert the probability of incident to tangible risk values to be presented to the LF leadership team.

### *3.4.3 Results for all LF Factories*

Figure 5 shares the overall trend of incident probability across the LF supply chain of approximately 13,000 active factories. Without weighting the data, the average probability of incident for an LF factory is 1.9%. When the calculation is weighted by FOB (factories which hold higher FOB are weighted more heavily than with factories with lower FOB), the average probability that a factory will experience an incident is 0.6%. The rest of this evaluation will focus on the factories with high probability of incident.

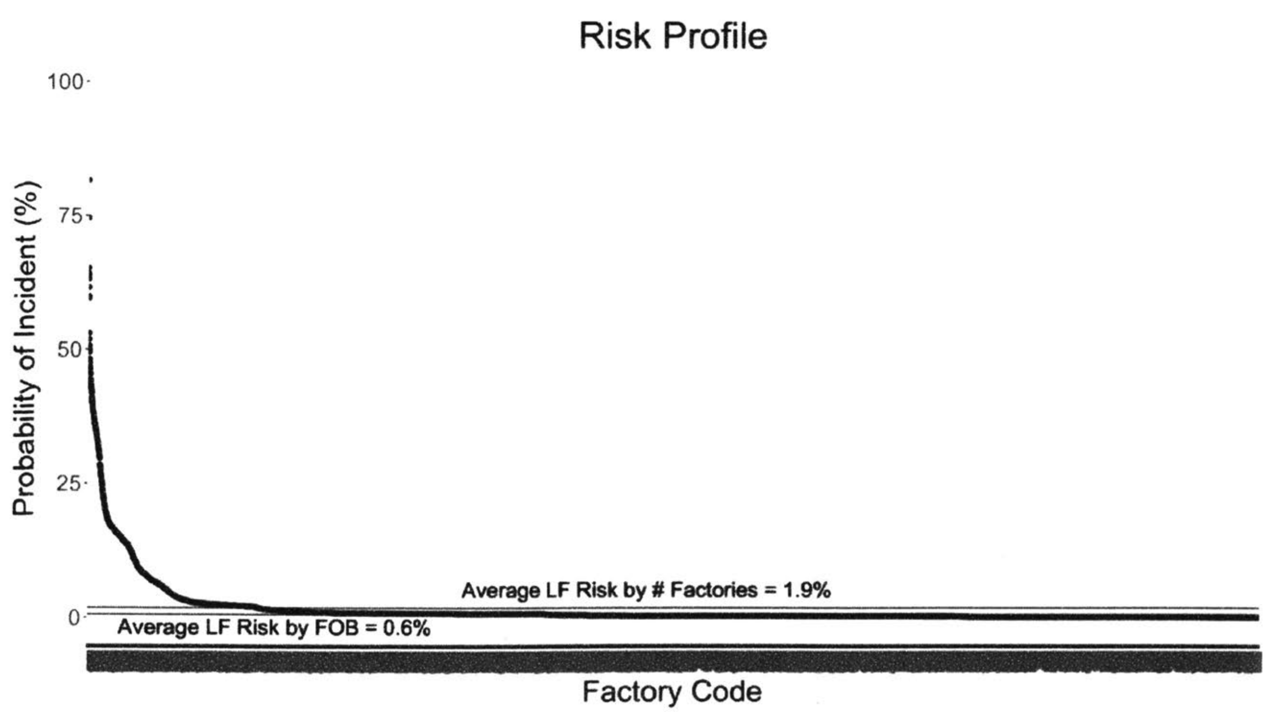


Figure 5: LF Risk Profile for all ~13,000 factories in supply chain

### *3.4.3 Results by Top 50 Riskiest Factories*

Next, the top 50 riskiest factories in the LF supply chain were evaluated. Figure 6 shows the probability of incident by the Factory Code, color coded by country. Note that the actual Factory Codes have been masked for confidentiality. The average probability of risk for this group of 50 factories is 46%. In this evaluation, the quantitative risk conversions reveal that LF would likely expend over 2300 labor hours to manage and mitigate the risk from these factories and approximately $1.4B USD of FOB would be put at risk. These quantified values do not include the risk taken on by the factory during an incident (significantly higher than LF risk), or the by the customer (varies drastically based on incident and product).

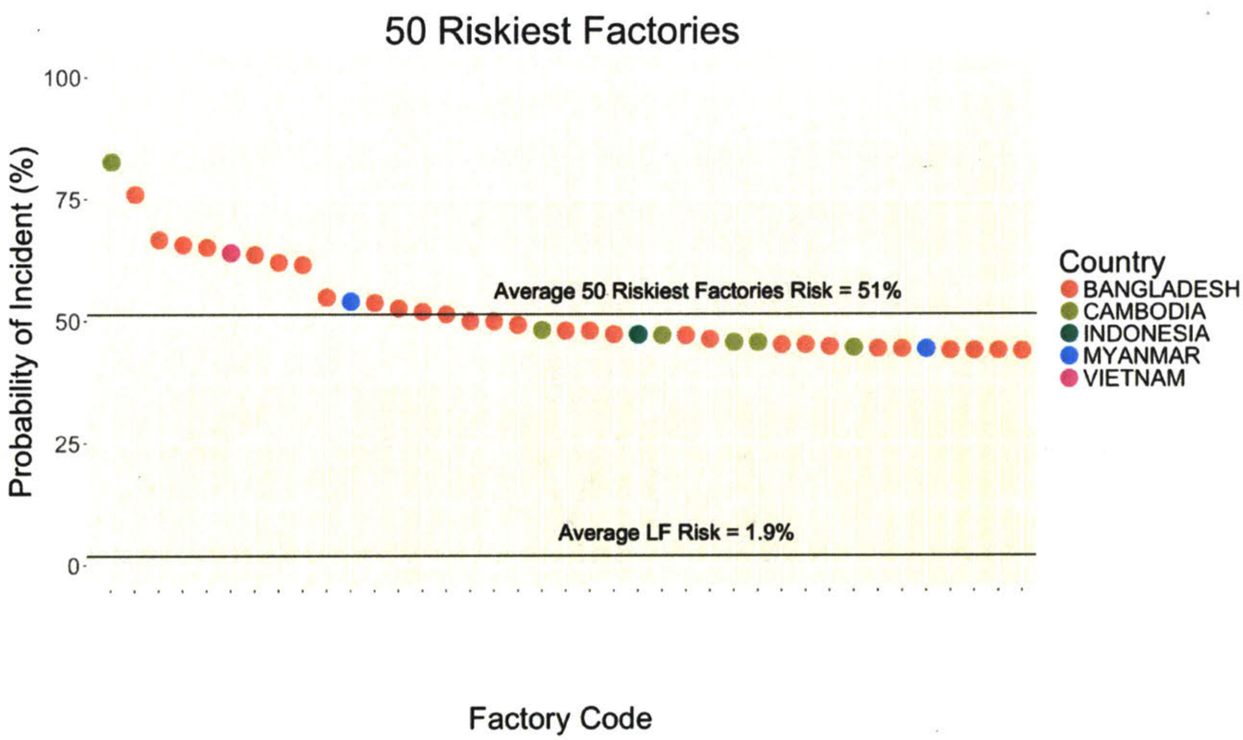


Figure 6: Top 50 riskiest factories in the LF supply chain

One shortcoming to the analysis presented in Figure 6 is that the reader cannot tell how *important* that factory is within the LF supply chain. For example, it's possible that the five highest probability factories hold very little product or make very easy-to-manufacture garments. In which case, LF may want to view supply chain risk through a different lens.

### *3.4.3 Results by Strategic Factories*

Below, an evaluation of "strategic" factories was performed, where "strategic" is defined as factories with annual FOB exceeding $100M USD. Here, the team uses FOB as a proxy for how *important* the factory is to the LF supply chain. Figure 7 shows the risk profile for the factories which meet this criterion. This type of evaluation provides the business with additional, more actionable data, which may help drive decision making regarding which factories to source from. Figure 7 represents over 900 labor hours of risk and approximately $560M USD worth of FOB.

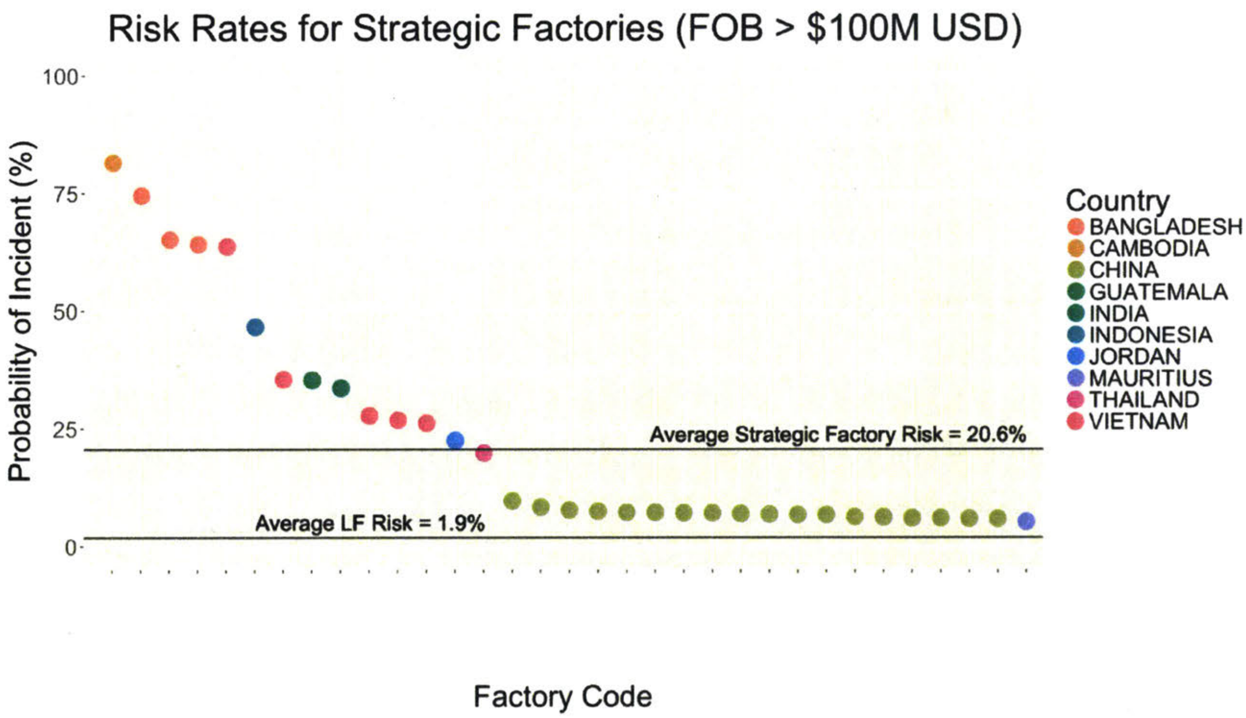


Figure 7: Evaluation of LF Strategic Factories (annual FOB > $100M USD)

### *3.4.4 Results by Incident Type*

The three types of incidents evaluated for the financial evaluation case studies included labor strike, health and safety, and unauthorized subcontracting. Figures 8, 9, and 10 (respectively) show the results of the model to predict which factories will experience these types of incidents. These models vary slightly from the model described above. The methodology is the same, but some of the significant metrics have changed to better predict each incident type.

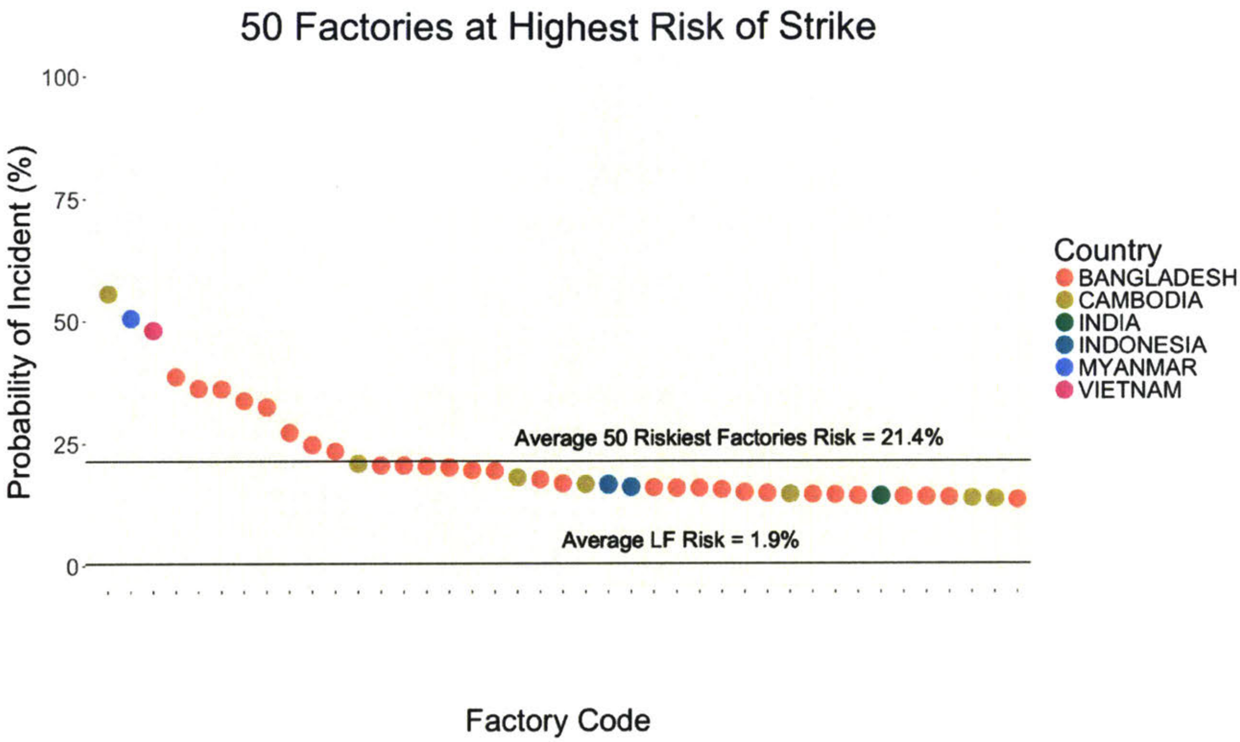


Figure 8: 50 factories at highest risk of a strike incident

Figure 8 shows the factories that are at high risk of experiencing strike incidents. This plot shows over 950 hours of LF mitigation efforts and approximately $500M USD in FOB at risk. One key takeaway from this plot is that Bangladesh is at high risk of strike incidents. This insight leads to additional questions, including curiosity around the Bangladesh labor policy, average wages, employment requirements, role of unions, etc. This data may be useful to the LF Bangladesh Country Team; as using this data they could help to inform a country wide initiative to understand and reduce the risk of strike incidents.


Figure 9: Factories at Risk of H&S Incident

Figure 9 presents the factories at high risk of experiencing a health and safety incident. The risk quantified within this evaluation is an estimated 950 LF labor hours and approximately $530M USD in FOB. The key takeaway from this plot is that again, Bangladesh is overwhelmingly the country most the highest risk of health and safety incidents. This insight could be valuable to various teams within the business when determining which factories to source from and which factories to invest in to reduce risk for LF and their customers. Additionally, it would be interesting to evaluate the Cambodia factory that is ranked as the most at risk; to identify what is causing that risk and how to best work with the factory to mitigate the probability of incident.

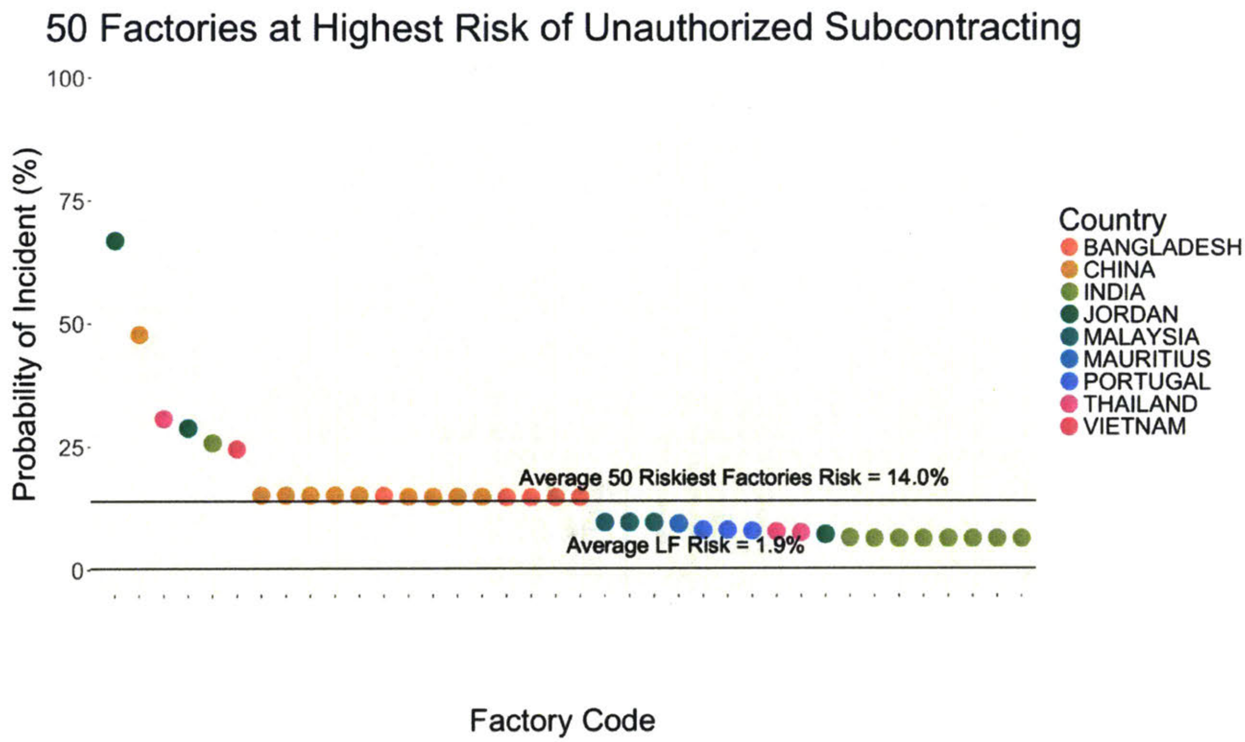


Figure 10: Factories at risk of Unauthorized Subcontracting Incident

Figure 10 shows the factories that are at the highest risk of an experiencing an unauthorized subcontracting incident. Unauthorized subcontracting has become an incident of interest within LF. Informally, the team hypothesizes that factories which perform unauthorized subcontracting activities are also at higher risk of more serious violations. As a side research assignment, this author assisted in reviewing and developing a pilot test to be completed by LF as part of a larger US Defense Advanced Research Projects Agency (DARPA) project. The project includes using detailed microbiome information collected from factories and distribution centers around the world to scientifically determine where garments were manufactured. Upon the successful completion of this pilot, the data provided in Figure 10 could be valuable to identify which factories to partner with to reduce the risk of unauthorized subcontracting.

### *3.4.5 Results by Customer*

Another way to evaluate the results of the model is to determine the risk of incident based on the LF customer. LF is organized such that major customers have teams dedicated to the production and logistics of their products. Therefore, viewing the results on a customer-specific basis might provide insights highly relevant to those teams. For confidentiality reasons, the names of the customers are not disclosed. The examples included in this section can be used to represent the varying ways in which the data and results can be represented, based on the business need.

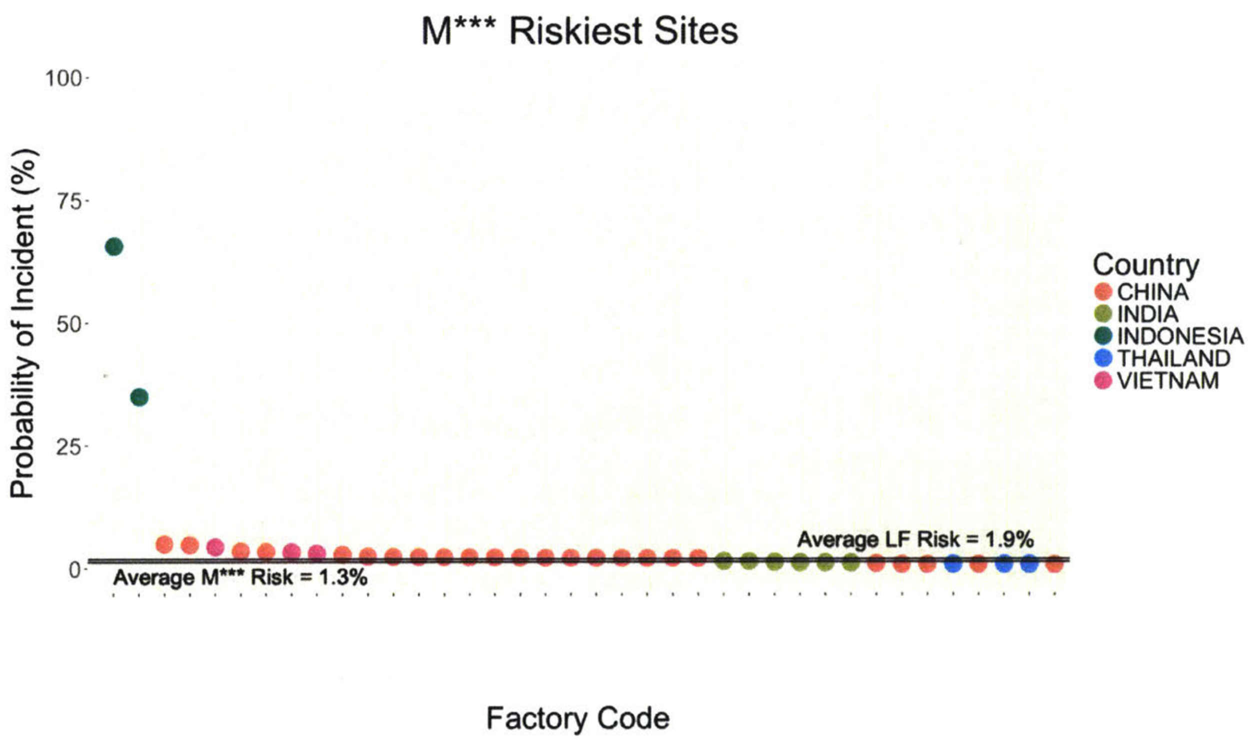


Figure 11: The risk profile for LF customer M***

Figure 11 presents the risk profile for confidential LF customer M***. Overall, the factories used for this customer result in a lower average risk (1.3%) than the average LF risk (1.9%). The LF team working with M*** may be interested in evaluating the relationships and opportunities partner with the riskiest two factories, shown to be located in Indonesia.

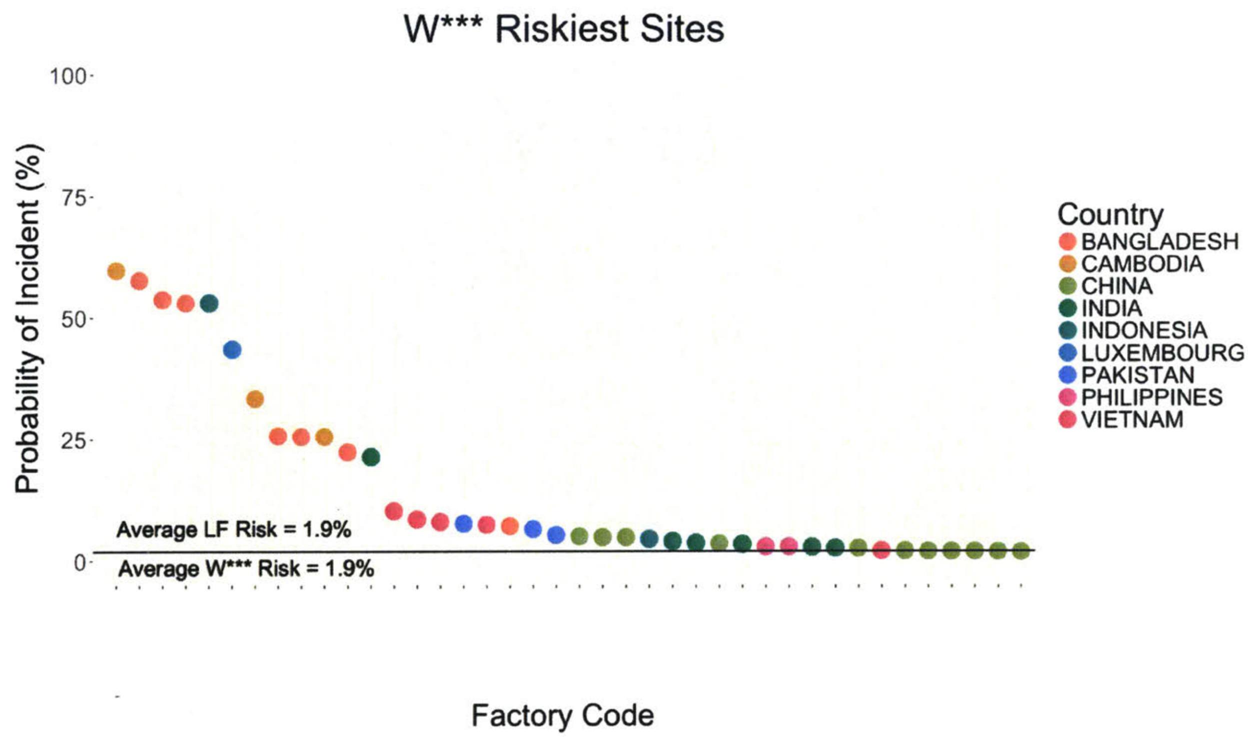


Figure 12: Risk Profile for W*** customer

Figure 12 represents the risk profile for the riskiest 50 factories with which confidential LF customer W*** works. This risk profile results in over 600 hours of man hours at risk and over $275M USD of FOB product. The factories used to source for this customer are more geographically diverse than that of the previous customer. The W*** team at LF may be interested in working with the high risk factories to reduce the risk of incident and build a more robust supply chain.

### *3.4.6 Results by Country*

An alternative way to analyze the results is by country. This may be relevant for certain parties within LF, such as the country managers and the compliance teams based within each country. As an example, the results for Bangladesh are shown in Figure 13, as Bangladesh reported the highest number of incidents to date. Plots of this nature could be created for each country, as dictated by the business need.

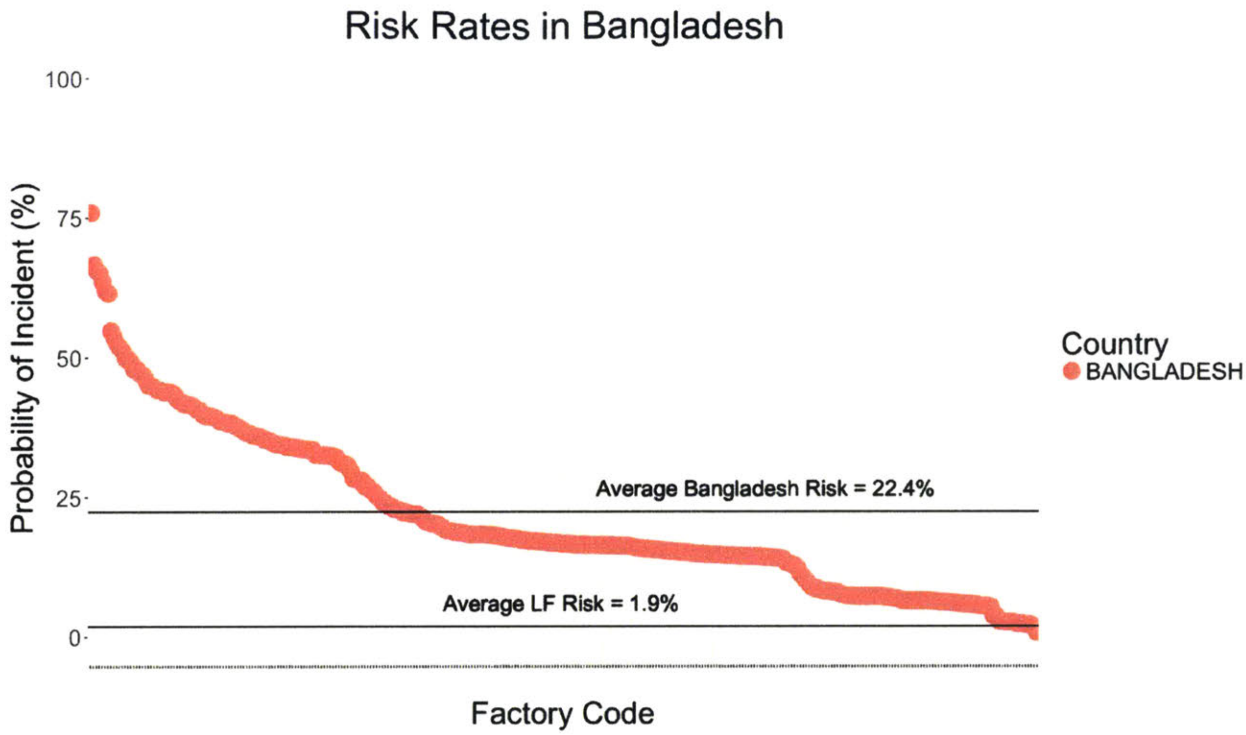

Figure 13: Factory Risk in Bangladesh

This plot shows every factory that LF contracts with in Bangladesh, and the associated probability of incident. This risk translates to over 7800 labor hours for LF to manage incidents, and to $2.8B USD in FOB product at risk. The Bangladesh teams may be interested in looking at strategic factories within this supply chain, identifying ownership trends between factories, and evaluating regions within the country as a more granular variable. There are many possible opportunities for action based on this type of plot. Also, note that the stepwise changes in this plot are likely due to the categorical variables used in the analysis (most notably the FOB ranges) or the imputation required to complete the dataset and run the analysis. With increased historical data and improved accuracy, the stepwise results shown should reduce.

### *3.4.7 Results by Operating Group*

Another method used to analyze the results is to structure the results by LF operating group. At the time of this analysis, LF operated nine operational arms, each focused on a different region of the world or product types. The operating groups include: LF Asia Direct (LFAD), LF Americas (LFAM), LF Europe (LFEU), LF Beauty (LFB), LF Furniture (LFF), LF Sweater (LFP), and Supply Chain Solutions 1, 2, and 3 (SCS1, SCS2, SCS3, respectively). The operating groups have separate organizational trees. Therefore, depending on an employee's location with LF, they may be interested in viewing the results by operating group. Figure 14 shows the results for the LF Americas operating group, as an example.

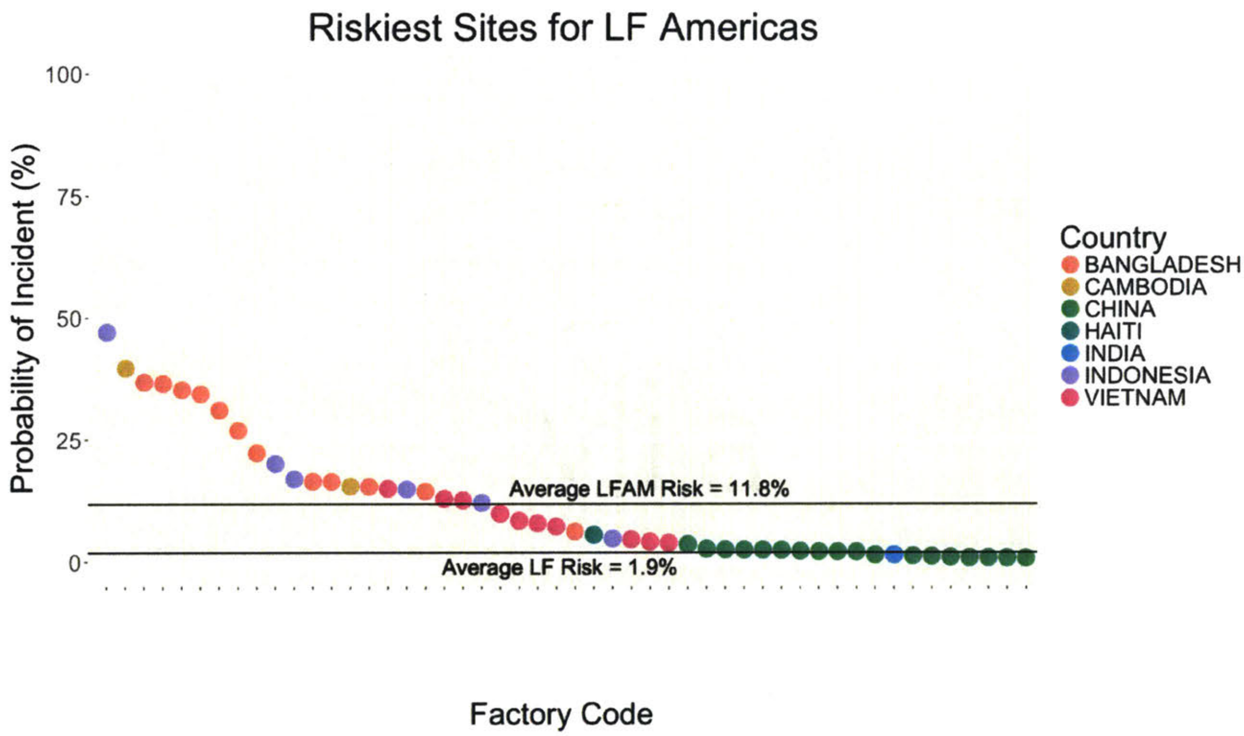

Figure 14: Riskiest Factories for LFAM Operating Group

The results indicate that some of the riskiest factories for the LF Americas supply chain are primarily located in Indonesia, Bangladesh, Vietnam and China. Depending on the industry trends, consumer demands, and relationships, the LFAM team can determine which factories to partner with to reduce their group's probability of experiencing a costly incident.

### *3.4.7 Interpreting Correlations by Significant Metric*

The final analysis technique to explore the results of the model is to evaluate the impact that each significant metric has on the probability of incident. Alternately explained, it is possible to visually analyze the correlation between the probability of incident and the significant metric. For example, Figure 15 shows the impact of FOB on the probability of incident. This plot includes data for all 13,000 factories.

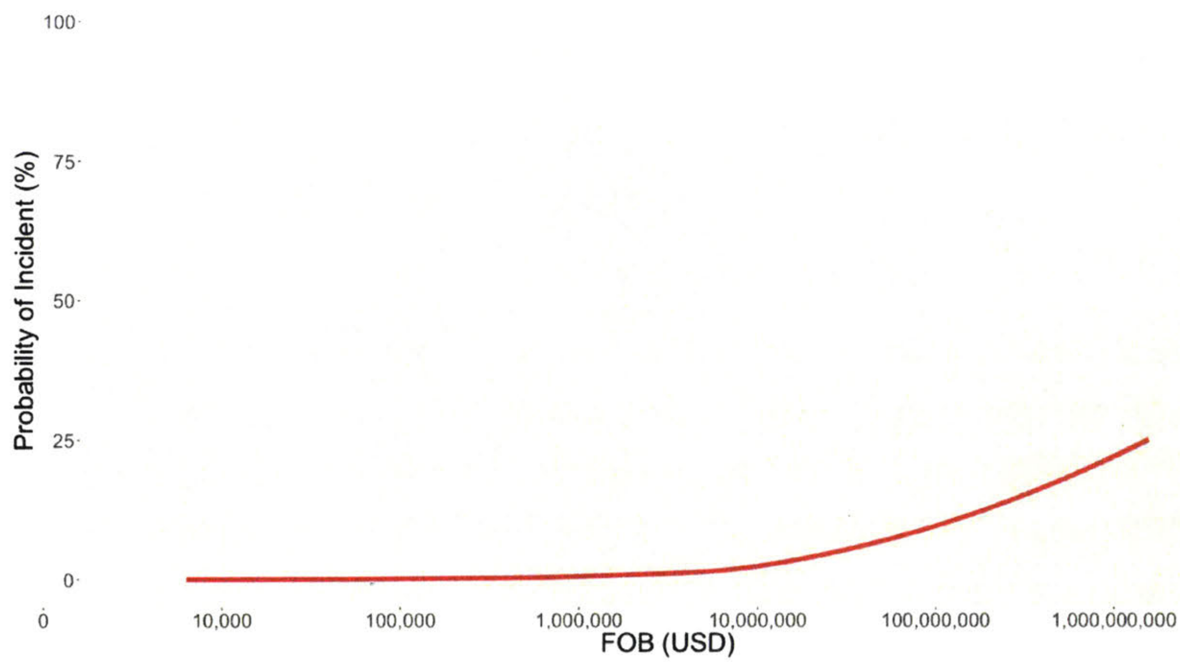


Figure 15: AS FOB increases, the probability of incident increases

Figure 15 shows a clear correlation: as FOB within a factory increases, the probability of incident increases. At first glance, this correlation may be accurate. One explanation of this correlation could be as follows: hypothetically, factories which manage large orders may be the largest factories (with more space, equipment, and personnel), and within large factories, there are more opportunities for an incident to occur.

However, in discussing this result with LF leaders, the *actual* trend may be contradictory (as FOB increases, the probability of incident *decreases*), for the following reasons:

1) Large factories tend to have established compliance teams and procedures. This suggests that incidents are closely tracked and reported. This contrasts with small factories, where there may not be designated safety or compliance officers, and incidents may not be reliably recorded. In conclusion, it may *appear* that large factories experience more incidents, when in actuality, this is because all of their incidents are recorded.
2) LF frequently places representatives at factories with large orders, to assist with achieving production metrics such as quality or compliance. In these cases, the LF representatives will report incidents to the LF compliance team at the time of the event. In comparison, LF will

not place representatives at small factories completing small orders; meaning incidents at small facilities may go unreported.

3) This correlation is in direct conflict with previous studies performed at LF, which found that larger factories are safer due to the defined procedures, frequent audits, and functional compliance systems.

This conflicting trend raises natural questions as to the reliability of the model. FOB was indicated as a significant metric within the model. However, if the LF leadership team qualitatively believes that the correlation is inaccurate, this provides incentive for additional research, analysis, and evaluation. It is possible that the results or correlation may shift given more granular FOB data. Many of the conversations regarding the plausibility of this correlation focused on the need for greater volumes of more accurate data. As the databases grow, and as the quality of data improves, the significant metrics and results of the model will change as well. It is possible that in future iterations of this model, FOB will not be a statistically significant variable.

As alluded to above, the FOB correlation assumes that large financial orders are fulfilled by "large" factories. To analyze that assumption in another way, Figure 16 shows the correlation between the number of workers and the probability of incident.

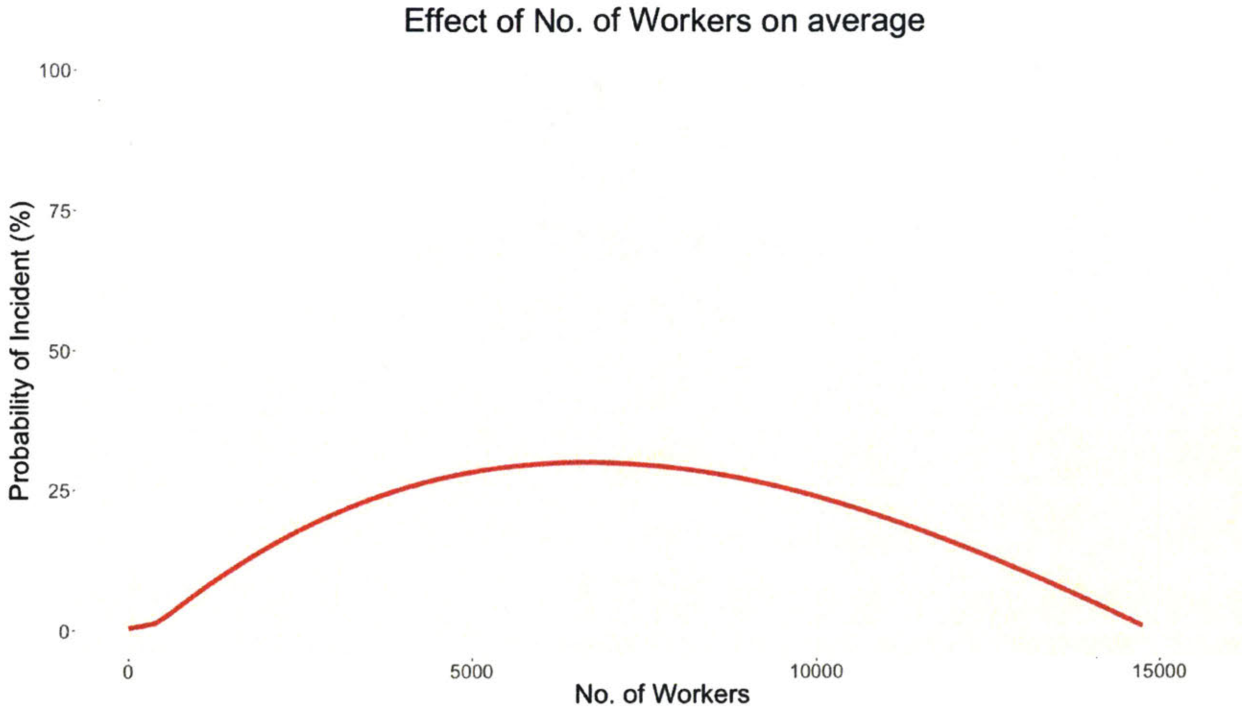

Figure 16: Effect of the number of workers on the probability of incident

This correlation led to additional questions and discussions. This plot indicates that as the number of workers in a factory converges on ~5,000 to ~10,000 employees, the risk increases, while at factory numbers outside of that range, the risk steadily declines. In the application of factory incidents, this means that the *medium-size* factories are the riskiest. Hypothetically, this can be explained by similar logic to the previous FOB correlation: as the factory size grows above 10,000 employees, the factory has dedicated compliance officer and established safety protocols, which create a safer factory environment. Similarly, in smaller factories, there are fewer people, less equipment, and smaller buildings, inherently reducing the risk of incident. This would imply that the medium-sized factories, (those that are too big to be managed by a small team, but too small to have a dedicated compliance officer) are the riskiest. However, this causation rationale is purely hypothesis. As previously discussed, the model can produce correlations but cannot provide causations.

Finally, a correlation between the quality of a factory's output and the probability of incident is provided. Prior to completing the analysis, it was hypothesized that as product quality increases, the factory risk will decrease. The team theorized that quality could be used as a proxy for good management and competent processes. Figure 17 presents the results of the correlation between the first final pass rate and the probability of incident. LF strives to achieve first final pass rate percentages as high as possible.

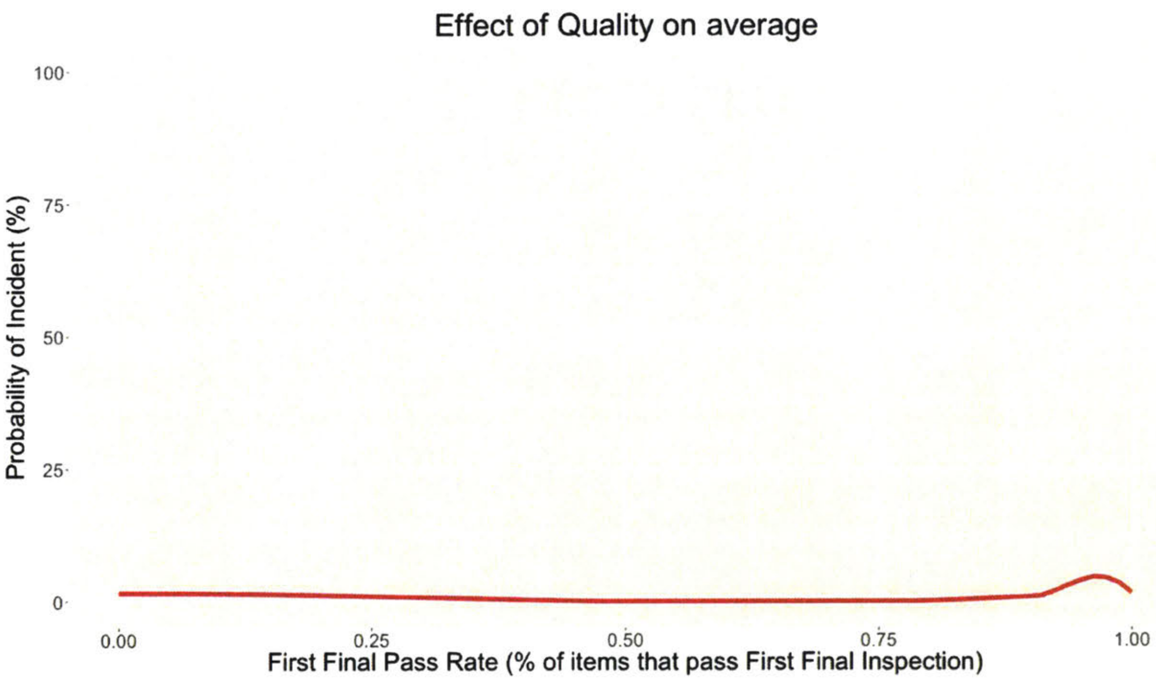


Figure 17: Correlation between the probability of incident and the quality metric "first final pass rate"

Inspecting this plot will show that as the first final pass rate percentage increases, the probability of incident decreases, as hypothesized. However, at the high end of the first final pass rate, around 90% - 100%, the probability of incident jumps up before falling back down. There are two hypotheses which provide rationale for this movement. The first is that some factories with high first final pass rates and high probabilities of incident skew the data at the tail end. This could raise questions regarding the accuracy of the quality data metrics, and how these metrics are measured and recorded at various factories. The second hypothesis is that LF deploys quality assurance officers to some factories to ensure that the output meets customer quality expectations. In the factories achieving the highest quality (97 – 100%), it is possible that LF does not send representatives, due to the high confidence that the factory has historically produced high quality products. However, in the factories in ~95% first final pass rate range, LF may send representatives, and those representatives onsite may record and report incidents, therefore skewing the probability of incident for factories in that quality range.

One final finding from the quality correlation is related to the strength of the correlation. As previously discussed, the team estimated that high quality may lead to fewer incidents, by means of a proxy and assumptions of what additional characteristics a high quality factory will maintain. However, the plot shows that quality is not highly correlated, as understood from the correlation line sitting lower than ~5% probability of incident throughout the plot.

### *3.4.8 LF's Guiding Metrics*

Prior to developing this tool, LF primarily used the factory audit ratings to determine the subjective and relative "safety" of a factory. It was anticipated that the audit ratings would provide a correlation to the probability of incident (as audit rating scores decrease, the probability of incident increases). However, in the many iterations of this model, the audit rating provided limited statistical significance at best. This is an important learning for LF, as it encourages reforming the audit processes to provide more accurate ratings. The VCS team is currently evaluating and pilot testing new audit methods and tools.

Another metric that the team hypothesized to be statistically significant is the level of capacity building completed at a factory. It was hoped that as the quality of training programs and the number of employees participating increased, the probability of incident would decrease. However, this metric was also not proven to be statistically significant in the model. This may be due to the small sample size (2%) of factories in the supply chain which have participated in capacity building programs.

# 4. Implementation at LF

The below section outlines how LF will use the model effectively in the future. Specifically, below are recommendations for how to use the model and how the model has performed so far.

## 4.1 Action Plan

This researcher developed an action plan to guide the VCS team in taking proactive steps to reduce the risk for strategic suppliers. The plan was developed through collaboration between Fung Academy and VCS, with expertise and input from individuals working on data analysis, factory communications, supplier compliance, and incident management. The formal action plan, which includes both short-term and long-term recommendations is attached in **Appendix 3**. The plan outline and desired intentions and outcomes are provided below. The success of the action plan is highly dependent on *engagement* from both the LF business units and the factory ownership. At the time of this writing, the recommendations in the action plan have not been tested with LF management or the factories.

## 4.2 Performance to Date

Following this researcher's departure from LF, the results of the model have been studied against new events. The following conclusions were reached regarding the model's performance when compared to test data (not included in the model development) from November 2017 to February 2018:[36]

- The top 50 riskiest factories at LF (from Figure 6 previously), accounted for 15% of the incidents which occurred during the November 2017 to February 2018 timeframe. However, expanding this range of factories to the top 1% of LF's riskiest factories (~136 factories) increased this percentage to 27%, and evaluating the top 5% of LF's factories (~680 factories) increased this percentage to 83% of incidents correctly predicted. The top 5% of LF's riskiest factories account for all factories with a probability of incident above 7.55%.

[36] (Andreev, 2018)

- The LF supply chain has experienced 41 incidents in the four months within this timeline. 11 incidents (27%) were predicted in the top 1% of LF's riskiest factories, 23 incidents (56%) were predicted in the top 5% of LF's riskiest factories, and seven incidents (17%) were not predicted.
- During this timeframe, Bangladesh experienced 19 incidents, Indonesia experienced ten incidents, China experienced six incidents, Vietnam experienced four incidents, and Cambodia and Guatemala both experienced one incident. Within the top 5% of LF's riskiest factories, Bangladesh was predicted to experience 18 incidents, Indonesia was forecasted to experience nine incidents, and China was expected to experience one incident. This means that in China, only one out of six incidents were accurately predicted. This points to potential inconsistencies in the model, likely regarding the Chinese country-level data. As discussed, this could be the result of a lack of granularity in the data, especially for a country of China's comparably expansive size in the region.
- The model states the 96% of factories in Myanmar and 79% of factories in Bangladesh have a high (within the top 5% of LF's riskiest factories, with risk profiles greater than 7.55%) probability of experiencing an incident. Conversely, Chinese factories have a probability of 0.2% of experiencing an incident, and Indian factories have a probability of 0.4% of experiencing an incident. This data was used in working with a Business Unit leader to understand the country level risks of working in certain countries, including guidance as to where to expand.
- An LF team member working directly with a brand requested use of the model to determine if and to what location the brand and LF should consider expanding production.
- Further analysis of the relationship between FOB and factory risk, with the recent data, showed a very strong correlation, consistent with earlier evaluations. This correlation continues to raise questions within LF, as expected. Figure 18 shows the recent evaluation in four countries. The consistent trend of FOB (blue lines) to reduce in risk from left to right across the plots shows the strength of the correlation. The variability of number of workers (orange lines) in each graph shows the comparably less significant correlation for this variable.

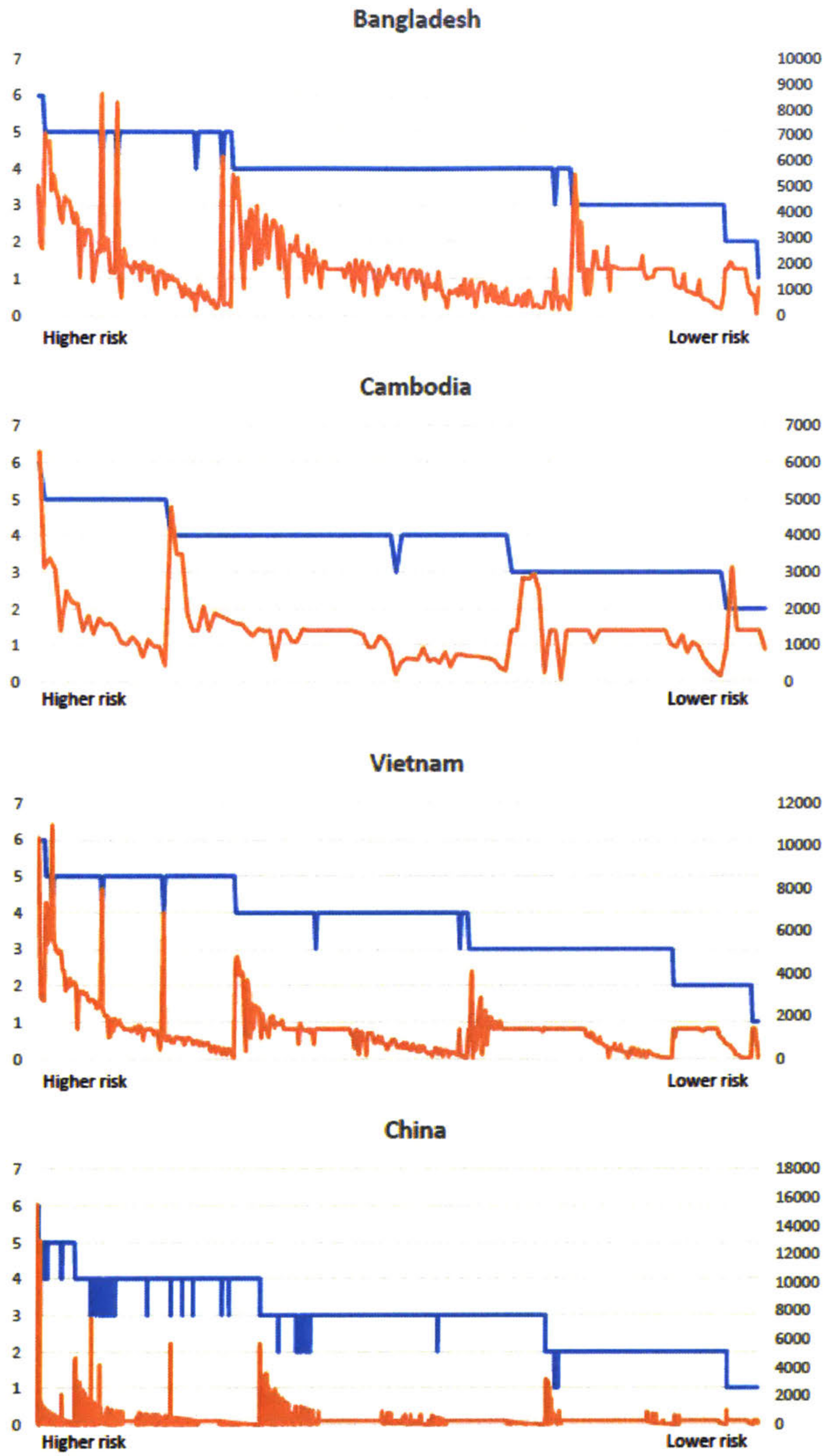


Figure 18: Country level analysis shows the strong correlation between FOB and factory risk and shows a weaker correlation between the number of workers and factory risk.

# 5. Conclusions

This section describes the challenges reached in developing this model, addresses the potential for future work in this area, and draws conclusions on the work conducted.

## 5.1 Challenges

Several challenges were identified through the process of developing and running the model. These challenges provided essential feedback to LF, primarily regarding the structure of the relationships with factories and LF's data management strategy. The following challenges were identified:

- **Incentives:** Factories are minimally incentivized to share data with LF. The factories are under contract with LF with limited formal obligation to submit data. Factories prefer to keep data confidential out of fear that if they report an incident or provide unimpressive data, LF will terminate the relationship. Generally, this is not how LF operates. LF would much prefer to work directly with the factory to improve operations. However, if the factory is committing a zero-tolerance offence, such as using child labor, the relationship will be terminated. As a result, factories are often afraid to share *any* data with LF, for fear of repercussions.

- **Data:** This predictive model (and LF's future data endeavors) will improve with greater volumes of more accurate data. There are multiple data sources used within the model, with various recommendations on how to improve:
    - Incident data: The earliest incident data available is from June 2016. Given the difference in magnitude between the number of factories and the number of annual incidents, there is room for the model accuracy to improve as greater historical incident records are collected. Additionally, developing an easier, more straightforward and comprehensive incident data collection process would improve the accuracy and reliability of the data that is available.
    - Factory data: The factory data is collected from the factories via audits, surveys, or informal conversations. As a result, the information which is available within

the LF database is incomplete and inconsistent. One way to solve this challenge is by implementing the new real-time observation program that the VCS team is piloting. Under this system, all stakeholders (including LF employees, factory management, factory employees, and customer representatives), are empowered to report issues at the factory level (compliance, safety, quality, etc.) in real-time, over their mobile phones.

  - EIU: The EIU data provides data at the country level. However, for large countries such as China, the standards, politics, regulations, expectations, and opportunities can vary widely between regions. Additional granularity, starting with large markets such as China would be beneficial in further understanding the impacts of specific metrics. Currently, these metrics may be unintentionally diluting one another, if a metric like "financial risk" is high in one region of the country and low in another, but that detail is not captured in the data.

- **Management Quality:** At the start of this research, it was hypothesized that management quality would be a proxy to estimate the probability of incident. Throughout model development, the team could identify neither an accurate existing measure of factory management quality nor a precise method with which to measure quality. Further investigation led this author to the research conducted by Van Reenan et al. As presented briefly in the literature review, the economists developed a comprehensive interview-based evaluation tool to measure management quality. The tool proved to accurately measure management quality across major productivity metrics. This type of system could be used within LF to develop accurate management quality measures for factory management teams. Note that interviewers used in the research were highly educated and well-trained, resulting in a cost of approximately $400 USD per 45-minute interview. Because this is a significant financial and time commitment, LF may use the research in other ways; such as evaluating the 18 open-ended questions used in the interviews, adapting them where appropriate, and piloting new variations to develop a quantitative measure of management quality.[37]

[37] (Bloom, Lemos, Sadun, Scur, & Van Reenan, 2014)

- **Correlation without Causation:** As discussed, predictive models can provide the user with valuable information regarding the correlations of variables to the model results. They cannot provide information on causation. As a result, the hypotheses developed and correlations derived from this model offer many questions for future analysis. For example, why is FOB statistically significant? Why are the audit rating and capacity building data not statistically significant? What additional insights are hiding within the results?

## 5.2 Future Applications and Work

The first version of this model was completed using accessible, historical, LF data. In the future, there are many more potential applications to improve upon this model, including:

- **Additional Data:** As LF and their factories continue to identify more data sources and collect supplemental data, the ability to recognize trends and predict future states will become more accurate. It is likely that there is additional data within LF which could be added to supplement the model as it currently stands. Seeking out, exploring, and adding this data where appropriate may provide addition insights.

- **Timing:** Feedback from LF leadership included a strong desire to understand *when* the predicted incidents will occur. Currently, the model is built without a timing component. This means that the probability of a factory experiencing an incident is not tied to an estimate of when that incident will occur. In order to understand *when* the incident will occur, the model may be updated to a more complex algorithm. The addition of this timing estimate would be highly valuable within LF.

- **New IoT and Data Applications:** One way to explore additional data collection and analysis is to identify new factory technologies and enable easy implementation of these solutions. Low technology solutions such as tracking quality data on a visual platform, installing energy monitoring systems, and designing operationally improved production lines were all successfully tested during this researcher's time at LF. There are ample additional opportunities to improve efficiency for factories and LF alike. Exploring these solutions will provide additional valuable data sources, empower the factory ownership teams, and raise margins for stakeholders.

- **Impact to Suppliers and Customers:** Another opportunity to improve this analysis is to focus on the impact to factories and customers. As previously mentioned, this analysis focused solely on the impact to LF, by calculating the labor hours and value of product at risk. However, it's likely that the factory incurs significantly more cost during and after an incident, in paying for structural repairs, medical bills, insurance premiums, overtime, late fines, rush shipping, etc. Additionally, depending on the severity of the incident, the customers may incur significant cost. If the products are shipped with poor quality, the customer's brand is threatened. If the products are late, the customer loses valuable time to sell the product, and finally, if a factory has an incident and is tied to the brand, their reputation could suffer greatly. Conducting additional research on the impact that incidents have to factories and customers would provide a better understanding of the overall risk of incidents and would provide a stronger business case to the factories and customers as to why predictive analytics is valuable.

- **Supply and Demand Forecasting:** Finally, this model predicts the risk of incidents. However, with the data available, there are opportunities to predict many more operational metrics. One example is to more accurately forecast supply and demand. Currently, there is very little structured supply and demand planning at the factory level. However, by analyzing historical data of previous orders, seasonality, brand habits, etc., factories could more effectively hire employees, plan overtime, and reduce variability in their production schedules.

## 5.2 Conclusion

As supply chains continue to gain complexity and squeeze suppliers, it will become more critical to collect, manage, and analyze data to identify operational improvements. One way to leverage this historical data is to predict future conditions, as was discussed in this thesis.

This predictive model developed through this research provides LF with a probability of incident for every factory in the supply chain. As discussed above, the results have proven to be reasonably accurate, with valid questions raised regarding the significance and correlation of some variables. These details and complexities are important to note within any model, however, the greatest learning for LF is having an understanding of the riskiest factories in their supply chain. These factories may or may not experience incidents in the near future; however, because they have been flagged, LF can take action to mitigate the potential risks.

For organizations like LF and the factories they work with, there are ample opportunities to improve available data access and collection, primarily through improving accuracy, focusing on the correct metrics, and gathering greater volumes of historical information. By implementing low technology solutions at the factory level, creating operational changes, and building trusting relationships between the stakeholders, LF can drive change in the industry to create a safer and more robust supply chain.

# 6. References


Andreev, D. (2018, February). *Model Output - Risk Prediction Analysis.* Shanghai, China: VCS Team, LF.

Bloom, N., Lemos, R., Sadun, R., Scur, D., & Van Reenan, J. (2014). *The New Empirical Economics of Management.* National Bureau of Economic Research.

Chopra, S., & Sodhi, M. S. (2004). Managing Risk to Avoid Supply-Chain Breakdown. *MIT Sloan Management Review,* 53-61.

Economist Intelligence Unit. (2017, November 1). LF Operational Risk Dataset. London, United Kingdom.

ESD. (2017, Term 5). Statistics: Week 11 Recitation, Logistic Regression. Unpublished.

*Freight on Board.* (2018). Retrieved from Investopedia: https://www.investopedia.com/terms/f/fob.asp

*Fung Academy.* (2018). Retrieved from About Us: https://www.fungacademy.com/page/about-us

*Fung Group.* (2018). Retrieved from Our Heritage: http://www.funggroup.com/eng/about/heritage.php

*Fung Group.* (2018). Retrieved from Management: http://www.funggroup.com/eng/about/management.php

Gallo, A. (2016, February 16). A Refresher on Statistical Significance. *Harvard Business Review.*

Giunipero, L. C., & Eltantawy, R. A. (2004). Securing the Upstream Supply Chain: A Risk Management Approach. *International Journal of Physical Distribution & Logistics Management, 34*(9), 698-713.

Greenhouse, S., & Harris, E. A. (2014, April 21). Battling for a Safer Bangladesh. *The New York Times.*

Hardesty, L. (2017, April 14). *Explained: Neural Networks.* Retrieved from MIT News: http://news.mit.edu/2017/explained-neural-networks-deep-learning-0414

Hudson, M. (2017, July 13). *What Does FOB Stand For?* Retrieved from The Balance: https://www.thebalance.com/retail-shipping-terms-fob-2890156

J.C. (2012, December 6). Garment Factory Fires: A "Distinctly South Asian" Tragedy. *The Economist.*

Jiang, B., Baker, R. C., & Frazier, G. V. (2009). An Analysis of Job Dissatisfaction and Turnover to Reduce Global Supply Chain Risk: Evidence from China. *Journal of Operations Management, 27*, 169-184.

Karen. (2018). *Seven Ways to Make up Data: Common Methods to Imputing Missing Data.* Retrieved from The Analysis Factor: https://www.theanalysisfactor.com/seven-ways-to-make-up-data-common-methods-to-imputing-missing-data/

Karen. (2018). *The 13 Steps for Statistical Modeling in any Regression for ANOVA.* Retrieved from The Analysis Factor: https://www.theanalysisfactor.com/13-steps-regression-anova/

Labowitz, S., & Baumann-Pauly, D. (2014). *Business as Usual is Not an Option: Supply Chains and Sourcing after Rana Plaza.* New York City: NYU Stern: Center for Business and Human Rights.

Mar, P. (2017, June). Director of Supply Chain Futures. (R. Schmidt, Interviewer)

Markham, K. (2014, November 19). *ROC Curves and Area Under the Curve Explained.* Retrieved from Data School: http://www.dataschool.io/roc-curves-and-auc-explained/

Miller, J. (2017, August). Executive Vice President of Quality Assurance, LF Private Label. (R. Schmidt, Interviewer)

Ray, S. (2017, September 9). *Essentials of Machine Learning Algorithms*. Retrieved from Analytics Vidhya: https://www.analyticsvidhya.com/blog/2017/09/common-machine-learning-algorithms/

*scale*. (n.d.). Retrieved from RDocumentation: https://www.rdocumentation.org/packages/base/versions/3.4.1/topics/scale

Srivastava, T. (2014, June 10). *Introduction to Random Forest - Simplified*. Retrieved from Analytics Vidhya: https://www.analyticsvidhya.com/blog/2014/06/introduction-random-forest-simplified/

Steinberg, D. (2014, March 3). *What Data Scientists Split Data into Train and Test*. Retrieved from Salford Systems: A Minitab Company: https://info.salford-systems.com/blog/bid/337783/Why-Data-Scientists-Split-Data-into-Train-and-Test

*The Economist Group*. (2018). Retrieved from The Economist Intelligence Unit Limited: http://www.eiu.com/

United Nations. (2017, August 1). *World Atlast*. Retrieved from What is the United Nations Geoscheme?: https://www.worldatlas.com/articles/what-is-the-united-nations-geoscheme.html

Vendor Compliance and Sustainability (VCS) Team. (2017). *Investigation Management SOP Draft, V2.* Unpublished.

Vendor Compliance and Sustainability. (2017, June 12). *Investigation Management SOP Draft, V2.* Unpublished.

*What is Logistic Regression?* (2018). Retrieved from Statistics Solutions: Advancement through Clarity: http://www.statisticssolutions.com/what-is-logistic-regression/

Wu, T., Blackhurst, J., & O'Grady, P. (2007, April ). Methodology for Supply Chain Disruption Analysis. *Interational Journal of Production Research, 45*(7), 1665-1682.

Yuan, Y. C. (n.d.). *Multiple Imputation for Missing Data: Concepts and New Development (Version 9.0).* Rockville, MD: SAS Institute Inc.

# 7. Appendices

# Appendix 1:

## EIU Metrics and Descriptions

The below table provides information on the metrics and sub-metrics provided by the EIU to LF, to be included as external data metrics in the predictive model. This Appendix shows the data for Country "X" as an example of how the data is provided for one country and with the associated definitions for each metric.

| Country | Series | 2017q3 | Definition |
|---|---|---|---|
| X | Financial risk | 8 | Overall score financial risk score |
| X | 44. Devaluation risk | 2 | What is the risk of a major devaluation? |
| X | 45. Depth of financing | 0 | What is the availability and depth of financing in the local market? |
| X | 46. Access to local markets | 0 | Are there restrictions on foreign companies gaining access to local capital markets? |
| X | 47. Marketable debt | 0 | Is there a liquid, deep local-currency denominated fixed-rate medium-term (five-years or more) bond market in marketable debt (that is debt that is traded freely)? |
| X | 48. Banking sector health | 0 | What is the risk of a systemic crisis in the banking sector? |
| X | 49. Stockmarket liquidity | 0 | How liquid is the stockmarket? |
| X | Infrastructure risk | 13 | What is the risk that infrastructure deficiencies may cause a loss of income? |
| X | 61. Port facilities | 1 | What is the risk that port facilities will prove inadequate to business needs? Evaluate the risk based on three criteria: degree of obsolescence, maintenance and sufficient supply to meet demand. |
| X | 62. Air transport facilities | 0 | What is the risk that air transport will prove inadequate to business needs? Evaluate the risk based on three criteria: degree of obsolescence, maintenance and sufficient supply to meet demand. |
| X | 63. Retail and distribution network | 1 | What is the risk that the retail and wholesale distribution network will prove inadequate to business needs? |
| X | 64. Telephone network | 0 | What is the risk that the telephone network will prove inadequate to business needs? Evaluate the risk based on three criteria: degree of obsolescence, maintenance and sufficient supply to meet demand. |
| X | 65. Road network | 1 | What is the risk that the road network will prove inadequate to business needs? Evaluate the risk based on three criteria: degree of obsolescence, maintenance and sufficient supply to meet demand. |
| X | 66. Power network | 1 | What is the risk that power shortages could disrupt business activities? |
| X | 67. Rail network | 1 | What is the risk that the rail network will prove inadequate to business needs? Evaluate the risk based on three criteria: degree of obsolescence, maintenance and sufficient supply to meet demand. |
| X | 68. IT infrastructure | 0 | What is the risk that the information technology infrastructure will prove inadequate to business needs? |
| X | 69. Economic exposure to natural disaster risk | 0 | What is the risk that the economy will suffer a major disruption owing to a natural disaster in the forecast period? |
| X | 70. Cyber security, preparedness | 0 | Assess the risk that the country is not able to withstand cyber attacks. |
| X | Labour market risk | 29 | Are labour market factors likely to disrupt business operations? |
| X | 54. Trade unions | 2 | How much power do trade unions wield ? |
| X | 55. Labour strikes | 2 | How common are labour strikes? |

| Country | Series | 2017q3 | Definition |
|---|---|---|---|
| X | 56. Labour laws | 1 | How restrictive will labour laws be in the forecast period? |
| X | 57. Skilled labour | 1 | What is the risk that finding skilled labour will be a problem? |
| X | 58. Specialised labour | 0 | What is the risk that finding specialised labour skills will be a problem? |
| X | 59. Meritocratic remuneration | 1 | To what extent are increases in wages directly related to productivity increases? |
| X | 60. Freedom of association | 1 | What is the risk that freedom of association and right to collective bargaining will not be respected? |
| X | Legal & regulatory risk | 8 | Is the legal system likely to safeguard investment? |
| X | 22. Fairness of judicial process | 0 | Assess the extent to which the legal process/the courts can be interfered with or distorted to serve particular interests. |
| X | 23. Enforceability of contracts | 0 | Assess the risk that contract rights will not be enforced. |
| X | 24. Speediness of judicial process | 1 | To what extent is the judicial process speedy and efficient? |
| X | 25. Discrimination against foreign companies | 1 | Assess the extent to which the authorities favour domestic interest over foreign companies in legal matters. |
| X | 26. Confiscation/expropriation | 0 | Assess the risk of expropriation of foreign assets. |
| X | 27. Unfair competitive practices | 0 | Government policy on actively promoting competition and curbing unfair business practices in this country will be: |
| X | 28. Protection of intellectual property rights | 0 | The protection of intellectual property in this country will be: |
| X | 29. Protection of private property | 0 | Assess the degree to which private property rights are guaranteed and protected: |
| X | 30. Integrity of accounting practices | 0 | What is the risk that business financial statements are inconsistent or misleading? |
| X | 31. Price controls | 1 | Are price controls in place and what is the risk that these would be extended in times of economic stress? |
| X | Macroeconomic risk | 25 | Is the economy stable and predictable? |
| X | 32. Exchange rate volatility | 2 | What is the risk of exchange rate volatility? |
| X | 33. Recession risk | 1 | What is the risk that the economy will experience a recession in the forecast period? |
| X | 34. Price instability | 0 | What is the risk that the economy will experience price instability in the forecast period? |
| X | 35. Crowding out | 1 | What is the risk of crowding out as indicated by Domestic Public Debt/M2 ratio? (Use highest of current and forecast year data) |
| X | 36. Interest rate volatility | 1 | What is the risk of interest rate volatility in the domestic financial markets? |
| X | Political efficacy risk | 9 | Does the political cultural foster the ability of business to operate effectively? |
| X | 14. Policy formulation | 1 | Is the present/prospective government likely to espouse and implement open, liberal and pro-business policies for nationals and foreigners? |

| Country | Series | 2017q3 | Definition |
|---|---|---|---|
| X | 15. Quality of bureaucracy | 0 | Assess the quality of the bureaucracy across the following criteria: overall competency/training; morale/dedication; and compensation/status. |
| X | 16. Excessive bureaucracy/red-tape | 0 | How pervasive is red tape? |
| X | 17. Vested interests/cronyism | 1 | To what degree do vested interests/cronyism distort decision-making in the public and/or private sectors? |
| X | 18. Corruption | 0 | Assess the pervasiveness of corruption among public officials. |
| X | 19. Accountability of public officials | 0 | How accountable are public officials? Is recourse possible in the case of unfair treatment do safeguards/sanctions exist to ensure to ensure officials perform competently. |
| X | 20. Human rights | 1 | Is there a risk that this country could be accused of serious human rights abuses? |
| X | 21. Societal vulnerability to natural disaster risk | 0 | What is the risk that a country's socio-economic shortcomings will exacerbate the impact of a natural disaster in the forecast period? |
| X | Foreign trade & payments risk | 7 | What are the risks in getting inputs/money into or out of country? |
| X | 37. Trade embargo risk | 0 | What is the risk that the country will be subject to a trade embargo sponsored either by a major international organisation, a significant trading partner, or one or more of the G-8 countries? |
| X | 38. Financial crisis | 1 | What is the risk that a financial crisis could curtail access to foreign exchange for direct investors? |
| X | 39. Discriminatory tariffs | 0 | What is the risk of discriminatory tariffs? |
| X | 40. Excessive protection | 1 | What is the risk of excessive protection (tariff and non-tariff) in the forecast period? |
| X | 41. Capital account | 0 | Can investors move money in and out of the country with ease for financial transactions (capital account)? |
| X | 42. Current account convertibility | 0 | Can investors make payments for goods and services and access foreign exchange without restriction? (current-account convertibility) |
| X | 43. Capital controls risk | 0 | What is the risk that capital controls would be applied or, if already in place, tightened in time of economic or financial crisis? |
| X | Political stability risk | 10 | Are political institutions sufficiently stable? |
| X | 9. Social unrest | 1 | What is the risk of significant social unrest during the forecast period? |
| X | 10. Orderly transfers | 0 | How clear, established, and accepted are constitutional mechanisms for the orderly transfer of power from one government to another? |
| X | 11. Opposition stance | 0 | How likely is it that an opposition party or group will come to come to power and cause a significant deterioration in business operating conditions? |
| X | 12. Excessive executive authority | 0 | Is excessive power concentrated, or likely to be concentrated, in the executive so that executive authority lacks accountability and possesses excessive discretion? |
| X | 13. International tensions | 1 | Assess the threat that international disputes/tensions could negatively affect the economy and/or polity |
| X | OVERALL ASSESSMENT | 14 | Overall score. |

| Country | Series | 2017q3 | Definition |
|---|---|---|---|
| X | Security risk | 19 | Is the physical environment sufficiently secure? |
| X | 1. Armed conflict | 0 | Is this country presently subject to armed conflict or is there at least a moderate risk of such conflict in the forecast period? |
| X | 2. Terrorism | 1 | How likely is it that domestic or foreign terrorists will attack with a frequency or severity that causes substantial disruption to business operations? |
| X | 3. Violent demonstrations | 1 | Are violent demonstrations or violent civil/labour unrest likely to pose a threat to property or the conduct of business? |
| X | 4. Hostility to foreigners/private property | 1 | Assess the extent to which one of the parties in the armed conflict or demonstrations/civil unrest has specifically shown hostility to foreigners or private ownership |
| X | 5. Violent crime | 0 | Is violent crime likely to pose a significant problem for government and/or business during the forecast period? |
| X | 6. Organised crime | 1 | Is organised crime (see definition below) likely to be a problem for government and/or business? |
| X | 7. Kidnapping/extortion | 0 | Is government or business at risk from kidnapping and/or extortion? |
| X | 8. Cyber security, likelihood of attacks | 2 | Assess the risk of an attack occurring |
| X | 2.1. Terrorist groups | 1 | Do terrorist groups exist in this country and, if so, are they well-organised and effective? |
| X | 2.2. Violent acts | 1 | Are terrorist groups capable of regularly committing violent acts? |
| X | 2.3. Hostility to westerners | 4 | Are terrorist groups openly hostile to Westerners, including business interests? |
| X | Tax policy risk | 13 | Are taxes low, predictable and transparent? |
| X | 50. Stable regime | 1 | Is the tax regime clear and predictable? |
| X | 51. Discriminatory taxes | 0 | What is the risk that corporations will face discriminatory taxes? |
| X | 52. Level of corporate taxation | 1 | Is the corporate tax rate low or is the prevailing rate of corporate tax actually paid low? |
| X | 53. Retroactive taxation | 0 | What is the risk from retroactive taxation? |

# Appendix 2:

# LF Incident Categorization

| No. | Event | Health and Safety | Strike | Labor Issue | Public Affairs | Unauthorized Subcontracting | Environment | Other | Natural Disaster |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Fire | X | | | | | | | |
| 2 | Lay off | | X | X | | | | | |
| 3 | Benefit | | X | | | | | | |
| 4 | Raise wage | | X | | | | | | |
| 5 | Subcontract | | | | | X | | | |
| 6 | Traffic accident | X | | | | | | | |
| 7 | Physical abuse | | | X | | | | | |
| 8 | Collapse risk | X | | | | | | | |
| 9 | Child labor | | | X | | X | | | |
| 10 | Mass illness | X | | | | | | | |
| 11 | Delay payment | | X | | | | | | |
| 12 | NGO campaign | | | | X | | | | |
| 13 | Assault | | X | | X | | | | |
| 14 | Forced labor | | | X | | | | | |
| 15 | Not a incident | | | | | | | | |
| 16 | Production pressure | | X | | | | | | |
| 17 | Arrest | | | | X | | | | |
| 18 | Factory shut down | | | | X | | | | |
| 19 | Prison labor | | | | | X | | | |
| 20 | Sabotage | | X | X | | | | | |
| 21 | Wastewater | | | | | | X | | |
| 22 | Evacuation | X | | | | | | | |
| 23 | Isolated illness | X | | | | | | | |
| 24 | Suicide | | | | | | | X | |
| 25 | Discipline | | | X | | | | | |
| 26 | Fallen | X | | | | | | | |
| 27 | Electrical shock | X | | | | | | | |
| 28 | Personal concern | X | | X | | | | | |
| 29 | Free access | | | X | | | | | |
| 30 | Bribery | | | X | | | | | |
| 31 | Audit transparency | | | X | | | | | |
| 32 | Body search | | | X | | | | | |
| 33 | Explosion | X | | | | | | | |
| 34 | Employee dispute | | | X | | | | | |
| 35 | Drinking water | X | | | | | | | |
| 36 | Punishment | | | X | | | | | |
| 37 | Heavy injury | X | | | | | | | |
| 38 | Crime | | | | X | | | | |
| 39 | Flood | | | | | | | | X |

# Appendix 3:

# Action Plans for LF

LI & FUNG

# Action Plan: Reduce Risk for High Risk Suppliers

Updated: December 13, 2017

---

## Executive Summary

This action plan was developed to provide guidance for how Li & Fung (LF) should best manage high-risk factories. "High-risk factories" are defined as: *factories at risk of experiencing a compliance-related incident which could disrupt production.*

An "incident" is defined as: *an unplanned or unwanted event which has the potential to escalate or has already caused damage to any of the stakeholders within the supply chain.*

Using a statistics algorithm, the model described in this document **articulates the probability that each factory in the LF supply chain will experience an incident.**

The process described in this document is intended to reduce the probability of future incident. Currently, LF experiences approximately one incident every three days, across over 13,000 active suppliers in the supply chain. Annually, incidents cost LF approximately 12,000 hours to manage and mitigate, and put $2.5 million USD of product at risk. This document outlines the **short term actions** and **long term processes** that are recommended.

# Short Term Action Items: Managing High Risk Suppliers

## How does this model fit into LFIS?

This model is one piece of the greater LFIS (Li & Fung Index for Sustainable Sourcing) program. This model, in conjunction with the environmental foot printing tool and other data driven applications will be used within the LFIS data platform to advise the business in making decisions regarding supplier risk and supply chain performance.

Infosys has been contracted by LF to develop the LFIS platform with support from the LF IT department.

## How do we complete a Pilot Test?

In order to effectively use this tool in the future and to market it during business development opportunities, we need to complete a case study.

We propose to work with an interested business unit (BU) to complete the following:

1. **Identify a high risk factory with which to engage.** The decision of which factory to engage with is at the BU's discretion using the articulated risk from the model; it could be a factory with high FOB, with high risk, with the best BU relationship, etc.

2. **Quantify the risk that the factory is currently bearing.** This value will come from the model. This will serve as a benchmark to compare initial risk against final risk at the culmination of the case study evaluation.

3. **Begin engagement with the factory.** This includes working with the factory to understand the baseline status of the factory. Ideally, the factory will share data regarding operations, production, demand planning, etc. with LF to provide a comprehensive picture of the factory operations.

4. **Identify root causes.** Next, identify the root cause of the risk. Continue asking "why" until the root cause of the problem is apparent. Perhaps the labor unions are unhappy with employment agreements which leads to frequent strikes. Perhaps the factory has poor influent drinking water quality which leads to mass illnesses.

5. **Identify potential solutions.** Solutions will likely be customized per root cause. For example, if the labor unions are unhappy, LF can identify an internal specialist to review policies and help develop a mutually beneficial labor strategy. Another example is to assist the factory in making operational improvements.

6. **Implement solutions.** Solutions should be implemented as a collaborative effort between LF and the factory. In the end, the factory must take ownership over the improvements to ensure that they are sustainable and ongoing. The solution must include collecting data to measure key performance indicators (KPIs) to quantifiably show improvement.

7. **Re-calculate risk.** Once the changes are made, the model should be re-run to show a change in the probability of incident. Additionally, the BU should work closely with the factory to understand if, when, and why an incident occurs, following the collaboration.

8. **Use case study for business development.** The successful case study can be summarized to provide the business development teams with information regarding the successful analytics tool that LF created and uses to proactively mitigate risk.

9. **Continue!** Continue identifying high-risk factories to work with and help mitigate risk to create a more robust supply chain.

---

## How do we use the model in the short term?

In the short term, the model will be updated on a **quarterly basis**. The risk sheets will be sent to the presidents with a reminder that by digitizing our supply chain, we are now able to articulate risk at this level. Angel or Dima should be available to meet with the Presidents to understand the articulated risk.

From here, VCS should follow up with the Presidents to ask if they want to move forward in mitigating risk at one of the factories.

# Long Term Process: Managing High Risk Suppliers

## Step 1: Identifying High Risk Factories

As of November 2017, the 50 riskiest factories are provided in Figure 1, below. To update this list, run the predictive analytics model available in LFIS, with help from Dima (VCS) or Angel (Fung Academy). **Note: this model is not perfect. It uses a machine learning algorithm**

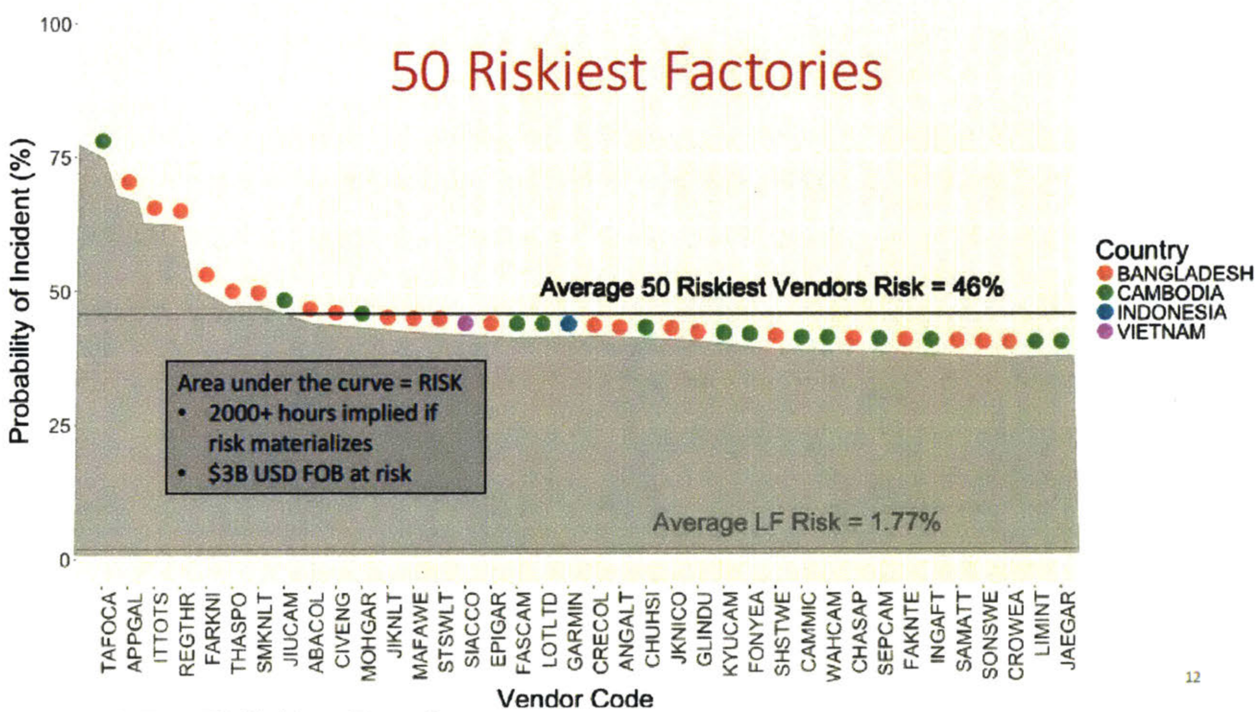


*Figure 1: LF Top 50 Riskiest Factories*

**to forecast which factories are most likely to incur an incident; however, incidents are often a result of human nature. Therefore, not all incidents can be predicted or avoided.**

The action plan discussed in this document is intended to reduce the risk of incident at suppliers and is recommended for the factories in Figure 1.

---

## Step 2: Engage with Business Units

After identifying high-risk factories, the first step is to engage with the LF Business Units (BUs). It is recommended that an automated email be sent monthly / quarterly from VCS to the BUs, stating the high-risk suppliers in their supply chain. Following the emails, VCS can follow up with the BU to review in detail.

It is critical for LF to understand the risk levels of their **strategic** suppliers. It may be beneficial to work with those factories first, especially if they will be more willing to engage than a peripheral supplier. The following topics should be discussed:

1. Explain the predictive model.

2. Describe the benefits for the factory, LF, and the customer if high-risk factories engage to mitigate incidents: (a) workers will be safer, (b) all stakeholders will save money through improved productivity, and (c) suppliers have the opportunity to gain more business.

3. Discuss relationship and improvement efforts with supplier management, including: (a) strategic position within LF's supply chain, (b) typical order size / frequency, (c) product mix and difficulty, (d) quality performance, and (e) previous improvement activities.

## Step 3: Send Written 'Engagement Request'

Once a high-risk factory has been identified, the Business Unit should send an 'Engagement Request' letter to factory leadership team. This letter should be written in the local language; a draft sample if provided in Appendix A.

This letter will request that the factory leadership team agree to a meeting with the LF team (Business Unit(s) and VCS). Following the letter, the Business Unit will follow-up with a phone call to the factory leadership team. The objective of this phone call is to schedule a face-to-face meeting between the supplier leadership and the LF team. The purpose of the meeting is to identify root causes of the high-risk rating and develop an improvement plan moving forward.

## Step 4: Engage Factory Ownership & Management in a Live Meeting

Once the factory has received the 'Engagement Request' letter and the phone call from the Business Unit there should be an in-person meeting. Attendees should include factory leadership, the LF Business Unit representatives and the LF VCS team.

During this meeting, it is important to build engagement and trust. The meeting facilitator should be skilled in engagement strategies and operational improvement techniques. Topics to be discussed during the meeting may include:

1. **Why this is important and what benefits the factory gains:** The factory leadership team must understand why it is important for them to lower their risk rating. By working toward a lower rating, the factory may:
    - Receive higher volume or more frequent orders from LF and customers
    - Build additional trust with LF and other customers
    - Create a safer working environment, engage employees, improve productivity
    - Avoid a costly future incident

2. **Predictive analytics model:** Explain that the model takes historical incident data from across all factories, and identifies correlations between these metrics and past incidents. These correlations forecast which factories are at risk. Confirm that the inputs used for this factory into the model are accurate (recent audit rating, number of employees, recent quality scores, etc.)

3. **Identify root causes:** Factory leadership and the LF team will share observations which should indicate opportunities for improvement for the supplier. Drill down to the root cause of the risk by asking "why?" until the root cause reached. *Every risk has a root cause.*

   **Outcome:** List of specific root causes creating risk for the supplier.

4. **Develop path forward:** Brainstorm potential solutions for each weakness. Potential solutions are shared below; however, customized, supplier-specific solutions should also be discussed in detail. For each solution, the following must be identified through an implementation plan:
   - Quantifiable key performance indicators (KPIs), which may include number of people trained, money saved, increase in product quality, etc.
   - A schedule which indicates start and end dates.
   - The individual who will be accountable or meeting this metric. Factory leadership should provide the support this person needs to be successful and achieve the goal agreed upon.

   **Outcome:** List of potential solutions, with implementation plans.

---

# Step 5: Mitigation Activities for Potential Implementation

Customized, supplier-specific solutions to address risk are highly encouraged. The following activities may be suggested to reduce risk. Every solution should be discussed in the context of that unique supplier, to allow for optimal engagement and improvement. Finally, these options can be bundled together to optimize supplier needs.

## Immediate Actions

1. **Data Collection & Monitoring:** If the factory has agreed to engage with LF, ideally they are also willing to share their data with us. Any data they have regarding quality performance, demand planning, operations, etc. Being able to track and monitor this data, and quantify progress, will help to identify the root cause of the risk.

2. **Initiate the Observation Development Program (ODP):** ODP is designed to equip LF quality and merchandising personnel with the skills required to observe and report compliance and sustainability concerns they see around the factory. This is a minor role added to their primary tasking at the factory, but can provide LF with valuable and continuous data regarding daily factory operations.

3. **Develop a Plan B:** The BU needs to consider what will happen if the risk cannot be mitigated at the factory. In some cases, it may be appropriate to terminate the relationship. To provide a smooth transition for the customer, LF must identify a factory to carry the required capacity and quality of production.

## Potential Long Term Solutions

These solutions should be customized based on the factory needs and root cause of the risk. Some options to consider are described below:

### General Compliance Risk

1. **Capacity Building:** If the factory believes additional training is required for management or employees, LF can offer capacity building courses designed to improve a target metric. Capacity building can be provided by LF or by an external provider, with certified proof of completion.

2. **LF Worker Mobile App:** If employee engagement is challenging for the supplier, the LF Worker Mobile App can be launched on the factory floor. The App is designed to engage employees by offering small pieces of advice, training, and encouragement throughout the work day. The App also tracks business metrics including time in / out and employee satisfaction. The App is still in development phase; as such there is limited quantifiable data available on how the App decreases risk.

3. **Operational Improvements:** If the supplier is at risk of engaging in unauthorized subcontracting activities, LF can offer (through the Fung Manufacturing Excellence Program - FMEP) to provide demand planning training or similar operational improvements to drive productivity effectively.

4. **Customized Solution:** Customized solutions should be developed to tackle specific problems and address precise metrics.

## Health and Safety Risk

5. **Fire Risk**
   **Potential Incident:** factory fire
   **Root Cause:** incorrect equipment operation, equipment overuse, exposed wiring, smoking, flammable material stored incorrectly, etc.
   **Solution:** educate factory management and employees on what to look for, how to mitigate, and how to resolve

6. **Structural / Construction Risk**
   **Potential Incident:** factory structural damage or collapse
   **Root Cause:** poor maintenance, faulty construction, or natural causes like flood / earthquake
   **Solution:** educate factory personnel to identify structural problems and adequately resolve the problem

7. **Food and Water Quality**
   **Potential Incident:** mass illness causing many people to miss work and slow / delay production

**Root Cause:** inadequate food preparation practices or poor water quality, among others
**Solution:** alter food preparation practices, install onsite water filtration, provide bottled water, etc.

8. **Work Related Injury**
**Potential Incident:** work-related injury such as carrying a heavy load which causes back injuries, or slicing one's hand while cutting fabric
**Root Cause:** limited protective equipment available, limited knowledge on the dangers of certain work, production pressure
**Solution:** education on risks and preventative measures, providing personal protective equipment (PPE), implementing engineering solutions (such as a cutting shield to protect operators)

## Strike Risk

9. **Layoffs, Delayed Payment, Stagnant Wages**
**Potential Incident:** employees strike because they are upset about layoffs, delayed payments or limited wage/benefit increases
**Root Cause:** factory labor policies are not in alignment with local force wants/needs
**Solution:** LF provide arbitration services between LF and labor force or labor union representatives to find mutually beneficial solution

## Unauthorized Subcontracting

10. **Unauthorized Subcontracting**
**Potential Incident:** factory subcontracts with another factory which is not authorized, putting the product at risk of poor quality and being developed under poor labor practices
**Root Cause:** production pressure, inefficient factory operations, poor demand planning, inability to apply for approved subcontracting
**Solution:** improve factory efficiency, improved demand planning, explain process to apply for approved subcontracting

## Labor Issue Risk

11. **Forced Labor / Abuse**

    **Potential Incident:** employees quit, are not productive, or are not working in acceptable conditions

    **Root Cause:** production pressure from upper management, inefficient factory operations

    **Solution:** improve factory efficiency, improved demand planning, educate factory management on acceptable work conditions, consider terminating future work

12. **Child Labor**

    **Potential Incident:** children working at the factory

    **Root Cause:** production pressure, access to cheap labor

    **Solution:** this is a zero-tolerance offense; stop working with this factory

## Public Affairs

13. **Factory Closure**

    **Potential Incident:** factory closes without warning which may create production problems for LF

    **Root Cause:** unknown; possibly lack of funding, fear of punishment due to poor labor practices, etc.

    **Solution:** educate factory management on proper budgeting, financing, labor practices, etc. to maintain consistent business practices and work flow

14. **NGO Campaign**

    **Potential Incident:** local NGOs raise awareness about poor practices at a factory, creating negative publicity

    **Root Cause:** factory is engaging in poor labor practices, NGOs misunderstood a communication, or NGOs supporting small stakeholder

    **Solution:** LF provide arbitration services between LF and labor force or labor union representatives to find mutually beneficial solution

### Environmental Risk

15. **Discharging contaminated wastewater**
    Potential Incident: factory discharges contaminated wastewater into a regulated body of water
    Root Cause: factory does not know about the regulation, factory does not know which technology or have access to the technology required to treat the water, factory does not have funds to pay for improvement
    Solution: educate the factory on local, relevant water regulations and applicable technologies; work with the factory to determine funding options

---

# Step 6: Follow Up & Evaluate Progress

### Follow Up

Once the improvement plan has been initiated, it is critical that the LF VCS team follow up with the factory leadership team. Follow up should be conducted at pre-defined intervals (i.e. quarterly) and must include quantifiable KPIs to prove that progress was accomplished.

### Evaluate Progress

Finally, evaluate the progress achieved by the supplier. Progress should be evaluated at the defined completion date, and by the quantifiable KPIs. If progress is achieved, new metrics for the supplier should be recorded within the LF database.

If progress is not accomplished, LF needs to re-evaluate the relationship with this supplier. Depending on the type of incident that the factory is most at risk for, actions can be determined. Altering expectations that factories do not need to show progress over time implies to the suppliers that LF does not take this initiative seriously and undermines these efforts.

### Backup Plan

In the event that LF decides to terminate the relationship with the vendor, the LF team needs to consider:

(1) Which supplier to move the customer's orders to (capacity, speed, quality, rating, ability)?

(2) What will happen to the deactivated factory, specifically the employees?

## Additional Opportunities to Reduce Supplier Risk

In addition to working directly with suppliers to address opportunities for improvement, LF can evaluate internal alternatives that may encourage factories to desire lower risk profiles.

**Trust and Incentives**

- **Commitment:** LF's relationships with suppliers are often transactional. Orders are placed on an as-needed basis, with little advance notice, due to a lack of LF demand planning. This means LF does not make long term commitments to the factories, and that orders may simply be sent to the low-cost supplier. This type of relationship does not incentivize factories to invest in performance improvement.
- **Data Sharing:** Another opportunity is to evaluate the incentive structure for suppliers to work closely with LF and share their operational data. If data, opportunities, and solutions can be shared across organizations, without the threat of punishment, we could drastically improve factory operations and conditions.

**Audit Structure:** Suppliers frequently experience "audit fatigue," caused as a result of having frequent, repetitive audits. LF should continue looking at ways to 'disrupt' the auditing process to streamline the data and results for suppliers and customers.

**Vendor Summit:** LF could host a "vendor summit" at an LF office. The objective would be to bring many local suppliers together and have a member of the LF leadership team share best practices and the future vision of LF – focusing on the intent to stay on the leading edge while redefining the garment industry supply chain. Focus on initiatives offered by LF that suppliers can take advantage of to improve their operations and increase their profits (i.e. FMEP, worker app, etc.)

# Appendix A: Draft 'Engagement Request'

LI & FUNG

Dear Sir/Madam:

We would like to request a meeting with you to discuss your facility's operations and potential improvements, in order to mitigate risk in your factory. Using data analysis, we have forecasted that your facility is at risk of experiencing an incident. By working with us through this process, you will see the following benefits:

1. Avoid costly incidents, penalties and media exposure
2. Improve collaboration with Li & Fung and its customers
3. Improve factory productivity, which may lead to higher profits

We estimate that your facility has a **XX% probability of experiencing an incident.** When an incident occurs in a factory, it can have significant impact on you, Li Fung, and customers. For the factory, this can result in higher costs, reduced profit, wasted time, or worker injury / fatality.

By working together, we can decrease this chance of incident. This letter is intended to start the process. In a few days, [insert local LF team member name] will call to schedule an in-person meeting with your leadership team, and with the LF Business Unit and local team. The goal of this meeting is to (1) reduce your risk by evaluating the root causes behind why your factory received a high probability of incident and (2) develop an implementation plan to reduce risk.

We look forward to working with you. If you have any questions, please reach out to your key point of contact at LF, or you can reach me at [insert Business Unit representative phone number].

Best,

[BU representative signature]

[BU representative name]

[BE representative contact info]