DATA-DRIVEN METHODS FOR THE RISK ANALYSIS OF GLOBAL SUPPLY CHAINS

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Supply chains have become more global due to the increased interconnectedness of the world's economy. As a result, companies in the U.S. are seeking more affordable overseas supply alternatives, though doing so may increase risk of domestic impacts when a disruption in the supplier's country occurs. It is then critical to assess the risks of global disruptive events to identify the cost effectiveness of overseas operations and risk management strategies. This work deploys statistical methods to predict the likelihood of a global supply chain disruption given a particular set of attributes related to the supplier characteristics and demographics, their risk management strategies, and their suppliers. The data analysis shows that the factors contributing to the likelihood of a disruption include the location of suppliers, the supplier resources to manage risk, and their insurance expenditure. Also, the Bayesian kernel model provided a higher accuracy than traditional statistical techniques. The outcome of the research provides decision makers with a flexible and reliable tool to predict the likelihood of disruptions and identify risk management practices that mostly impact the resilience of the company's supply chain.

I. INTRODUCTION

Supply chains are increasingly global due to the interconnectedness of the world's economy. As a result, companies in the U.S. have been seeking more affordable overseas alternatives for suppliers and manufacturing facilities. Oftentimes, such alternatives come with a high risk whereby a disruptive event in the supplier's country results in large scale impacts on the production and sales of the companies in the United States. For example, after the terrorist attacks of September 11, Ford and Toyota suffered from significant delays in parts delivery, and, as a result, they stopped their production[1]. Another example of a global supply chain disruption is the prolonged period of drought that hit Russia over the summer of 2010, where over one-fifth of the country's wheat crop had been destroyed, resulting in all grain exports being banned by the Russian government. As a result, General Mills products faced a significant cost increase of 4%-5% in September 2010 (Ref 2).

It is then critical to assess the risks and consequences of potential global disruptive events such as tsunamis, earthquakes, or factory fires, among others. In many cases, enterprises develop risk management strategies as a reaction to a disruptive event. For example, an explosion at an iPad manufacturing facility in China in May 2011 resulted in the death of two workers and the injury of over a dozen workers. In February 2012, Apple hired the Fair Labor Association to conduct audits of its final assembly suppliers[3]. In another example, a fire in a Philips Electronics plant in New Mexico interrupted the supply of critical cellphone chips to two major customers, Ericsson and Nokia. Nokia found an alternate supply source in three days at an upfront cost which paid off in a smaller impact of the disruption while Ericsson lost about a month of production resulting in approximately $500 million loss in its mobile phone division due to its lack of supply chain risk management[4]. As such, the accurate prediction of global supply chain disruptions plays a vital role in (i) assessing the cost effectiveness of overseas operations, and (ii) identifying risk management and preparedness strategies to proactively protect multinational corporations from disruption losses.

The main challenge encountered in this research is the availability of data due to (i) the rare occurrence of such events and (ii) the lack of disclosure of full information among industries and corporations. As a result, most studies focused on probabilistic risk analysis, simulation methods, or exploratory data analysis. This study analyzes survey data collected on the occurrence of a global supply chain disruption of almost 200 companies given multiple predictors related to their characteristics and demographics, risk management strategies, and suppliers.

The first objective of this work is to accurately predict the probability of a global supply chain disruption for a company given multiple sources of information. Bayesian methods, more specifically Beta Bayesian kernel models, are used to predict the probability given information on historical disruptions, company demographics and risk management strategies, as well as any other prior information gathered from the managers' expertise in the field. The second objective of this work is to identify the factors that mostly impact the probability of a global supply chain disruption happening in order to address effective resource allocation to mitigate or possibly avoid such risk. The stepwise regression method is used to identify significant attributes in the data to assess the impact of these variables on the risk of a disruption.

II. LITERATURE REVIEW

Supply chain risk has increased due to globalization as corporations seek the advantage of global low cost supply sources which is normally achieved in a stable environment, however, they may be facing the highest level of risk due to the cultural and institutional differences as well as the environmental risk exposure of their suppliers[5]. The combination of (i) an increase in global sourcing, (ii) the use of a global sourcing model, and (iii) the trends of higher levels of agility and responsiveness and lower levels of inventory, is leading to an increased potential and impact of global supply chain disruptions, and as a result, a greater interest in supply chain risk management research[6].

While supply chain risk management is commonly studied in the literature, empirical research work is still lacking[7, 8]. Research in this area is mostly concerned with a high-level perspective of supply chain uncertainty and risk perception which does not allow a more detailed analysis of key factors and variables that impact the likelihood of disruptions and ultimately supply chain risk management. A number of research studies have considered an empirical analysis to address this gap in the literature where the automotive industry has been the main focus of these studies. MacKenzie et al. (Ref 9) use a multiregional economic input-output model to assess the indirect impacts of the Japanese earthquake and tsunami on the auto industry. Another study[10] performed an empirical analysis of supply chain risk in the German automotive industry using a survey of 67 manufacturing plants and highlighted the vulnerability of globalized supply chains. In addition, the study analyzed the impact of different supply chain risk management approaches, in particular the authors consider two approaches, reactive and preventive, and conclude that companies with the former approach have an improved resilience while those with the latter approach have better flexibility and cost reduction. Another survey-based analysis[6] conducted semi-structured phone interviews across multiple industries to seek insights into issues regarding global sourcing and supply chain disruptions, more specifically, they focused on disruption discovery, disruption recovery, and supply-chain redesign. The empirical studies done in supply chain analysis have mostly focused on exploratory analysis and did not consider any statistical methods to pursue predictive analytics.

Supply chain risk managers recommend the use of predictive measures from statistical analysis to prevent losses from a disruption as an essential step in the process towards an effective supply chain risk management[11]. The ability to predict the probability of a supply chain disruption can also improve the supplier selection across a number of criteria[12]. As such, this paper expands on the exploratory analysis of survey-based data of global supply chain disruptions, and considers a statistical modeling approach to make predictions of future probabilities of a disruption given information on the enterprise and its risk management strategies. Such a capability will overcome the gaps identified in the literature and improve supply chain risk management. There has been little work done in that area in recent years. One study focused on motor carriers' ability to withstand disruptive events by developing a scoring tool similar to the credit score system as a means to quantify supply chain risk[13]. Other modeling efforts in that area can be found in a more thorough review of operations research and management science literature on supply chain disruptions[14].

The work proposed in this paper has broader multi-industry implications and is focused on the probabilistic estimation of a disruption occurring while accounting for the impact of the decision maker's prior knowledge in the Bayesian kernel models. Data-driven methods will revolutionize the way we approach supply chain risk analysis which is proven by a study based on a number of well-established theories[15], and this research is among the first steps in data-driven global supply chain risk analysis.

III. METHODOLOGY

In order to accommodate the scarcity of data, account for the uncertainty, and integrate the impact of attributes in the prediction of the likelihood of a supply chain disruption, we propose to use a Beta Bayesian kernel model[16].

Kernel-based approaches to data classification have revolutionized data mining[17]. Bayesian kernel methods have recently been introduced to the machine learning literature[18] providing probabilistic solutions as opposed to deterministic solutions. Bayesian kernel methods integrate (i) the Bayesian property of improving predictive accuracy as data are dynamically obtained, with (ii) the kernel function which adds specificity to the model and can make nonlinear data more manageable. Kernel functions are used to map input data, for which no pattern can be recognized to model their behavior, to a higher dimensional space, where patterns are more readily detected. Such functions enable algorithms designed to detect relationships among data in the higher dimensional space[19, 20]. On the other hand Bayesian methods make use of previous data to estimate posterior probability distributions of the parameter of interest that follows a specific prior distribution. As a result, the integration of Bayesian and kernel methods allows for a classification algorithm which provides probabilistic outcomes (i.e., probability of a data point belonging to a particular class) as opposed to deterministic outcomes (i.e., the mere classification of a data point to a particular class).

Most Bayesian kernel methods are developed with Gaussian prior distributions[21, 22, 23]. An important extension to the basic Bayesian kernel model is the non-Gaussian Bayesian kernel model[24, 25], which can improve the predictive accuracy for certain problems where a Gaussian distribution for model parameters should not realistically be assumed. MacKenzie et al. (Ref 16) highlight some of the drawbacks of using the Gaussian distribution for binary classification problems, use a Beta conjugate prior, and offer an alternative likelihood function to the logit. Their work expands on previous research done on Non-Gaussian kernel models[24, 25] by introducing a more generalized model based on the Beta conjugate prior which provides much faster computation time than traditional machine learning methods that rely on either optimization or simulation to find the solutions. Other extensions to non-Gaussian Bayesian kernel models have been developed to accommodate count data to estimate the frequency of disruptive events[26, 27, 28]. In this work, a Beta Bayesian kernel model is presented and deployed to estimate the probability of supply chain disruption, θ_i, Eq. (1). The Beta Bayesian kernel model developed by MacKenzie et. al (Ref 16) is reviewed here.

$$\theta_i|\mathbf{y},\ \boldsymbol{x} \sim \text{beta}(\alpha^*, \beta^*) \tag{1}$$

The Beta Bayesian kernel model is developed based on a conjugate prior. As such, both the prior and the posterior distributions of the parameter of interest, θ_i, are a Beta distribution with parameters (α, β) and (α^*, β^*), respectively. Eq. (2) shows the relationship between prior and posterior parameters which is used to classify the observations of an unknown data point *i* represented by the vector $\mathbf{x}_i$. The probability that data point *i* is positively labeled follows the beta distribution where y_i represents the unknown classification of data point *i* and $\mathbf{y}$ is a vector of *m* known classifications. The outcome of such a model would be the probability distribution of the parameter of interest. And a point estimate of that parameter could be the expected value of the posterior probability distribution or any other conditional expected value representing a more extreme case, which can be used to make predictions.

$$\alpha^* = \alpha + \frac{m_-}{m} \sum_{\{j|y_j=1\}} k(\boldsymbol{x}_i, \boldsymbol{x}_j)$$

$$\beta^* = \beta + \frac{m_+}{m} \sum_{\{j|y_j=-1\}} k(x_i, x_j) \tag{2}$$

The kernel function between the attributes of two data points is $k(x_i, x_j)$, and m_+ is the number of positive labels while m_- is the number of negative labels in the training set of size m. The ratios representing the proportions of each class insure an unbiased estimation of the posterior parameters in the presence of imbalanced data sets. In order to account for the impact of the covariates on the response variable, Mackenzie et al (Ref 16) proposed to use a radial basis kernel function which is commonly used in kernel-based machine learning techniques. We consider here a different function to accommodate categorical data, the overlap kernel[29], since the radial basis function is based on the Euclidian distance in the feature space which can result in a loss of information when used with categorical or binary data. The overlap kernel function works with single values only and not vectors. A univariate kernel, $k_0(x_{ik}, x_{jk})$, is first computed as a similarity measure between the values of an attribute, k, for the two data points, $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$. The function identifies "maximum similarity" if the values are equal, and "minimum similarity" if they are not equal, Eq. (3).

$$k_0(x_{ik}, x_{jk}) = \begin{cases} 1 & x_{ik} = x_{jk} \\ 0 & x_{ik} \neq x_{jk} \end{cases} \tag{3}$$

In order to compute the kernel between the vector of attributes for two data points, the univariate kernel, k_0, needs to be evaluated for all the attributes considered in the model, we denote d as the dimension of the dataset. As such, we obtain a binary vector, $\boldsymbol{u}$, of dimension d containing all the univariate evaluations of the kernel k_0, on the data points $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, Eq. (4).

$$\boldsymbol{u} = \{k_0(x_{i1}, x_{j1}), k_0(x_{i2}, x_{j2}), \dots, k_0(x_{id}, x_{jd})\} = \{u_1, u_2, \dots, u_d\} \qquad (4)$$

A composition function[29] is then used to compute the kernel value between the attribute vectors of the two data points. While there are a number of composition functions, we choose to use the average of all the univariate evaluations over the dimension of the dataset. The composition function would take a vector and return a scalar which is the kernel between two data points.

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \frac{\sum_{k=1}^{d} u_k}{d} \qquad (5)$$

A larger number of similar attributes will yield a large value for the kernel between the two data points and accordingly determine the probability distribution for the unknown parameter. Based on Eq. (2), a larger kernel between the attributes of the unknown parameter and the known data in the positive class will yield a larger value for the parameter α^* and as a result a posterior Beta distribution skewed to the left with the mass of the distribution concentrated on larger values of the unknown parameter, corresponding to a probability for a supply chain distribution closer to 1. On the other hand, if the attributes of the unknown parameter are similar to data points in the negative class, the kernel function in the formula of β^* in Eq. (2) will have larger values resulting in a right-skewed posterior Beta distribution with the most likely value of the probability of a disruption falling under 0.5.

IV. DATA

One of the main challenges of conducting quantitative analysis of global supply chain risk is the availability of data on historical disruptions as well as on the company's portfolio and risk management strategies. The research done in this paper used data from a survey conducted by the American Productivity and Quality Center in which 196 companies were interviewed. The response variable in the survey is binary and corresponds to whether or not the company had a supply chain disruption in the past year (i.e., $y_i = 1$ if a disruption occurred, $y_i = 0$ if there was no disruption). There are 42 attributes that can be classified into four main categories. The first set of attributes is concerned with disruption characteristics such as the impact of past disruptions and the company's concerns about future events. Another set of attributes is focused on suppliers characteristics such as their location, any change in the number of suppliers, the risk assessment method and frequency of assessment, the evaluation of their compliance with laws and procedures in their respective locations, and business continuity program. The third category of covariates is concerned with the supply chain risk management of the company such as the balance between sole and multi-sourcing, the resilience of the supply network, the supply continuity plan in the event of a disruption, the level of expenditures on supply chain risk assessment and insurance, the extent of an inventory cushion, and the presence of any relevant obstacles. Finally, some of attributes represent company characteristics such as its size (total recorded revenue), the location of headquarters, and the industry type.

The dataset is heavily imbalanced with 91% of the companies reporting a supply chain disruption occurring in the past year. As such, only the weighted version of the Beta Bayesian kernel model will be considered in the analysis, Eq. (2). Out of the companies that experienced a disruptive events, 62% have key supply chain partners in areas of the world that are considered risky with exposure to natural disasters, extreme weather, and/or political turmoil.

V. NUMERICAL RESULTS

As mentioned previously, the two objectives of this paper are (i) to provide accurate predictions of the probability of a supply chain disruption, and (ii) to identify the most critical factors impacting such probability. In this section, we present the numerical results of both analyses conducted to make accurate predictions and identify impactful variables.

V.A. Predictive Accuracy

As the data is heavily imbalanced towards the positive class, we only consider the weighted version of the Bayesian kernel model. Our choice for the kernel function to be the overlap function is due to the nature of the data being categorical, and we are left with the prior parameters to be determined. The choice of the prior is often overlooked such that the prior distribution is either noninformative or assumed to be known. In risk analysis problems, experts in the field can help assess any prior knowledge about the parameter to be estimated. Ideally, risk managers are interviewed, and using probability elicitation techniques[30], a prior probability distribution is defined. In this analysis, we consider three different prior distributions for the Bayesian kernel model, they are summarized in Table 1. The uniform and Jeffrey's are both considered weak priors and assume that the two prior parameters have the same value. The third model assumes an empirical prior which results in a strong assumption on the shape of the prior distribution of the parameter of interest. The empirical prior parameters are derived from the historical data using the method of moments where the theoretical mean and variance are set to be equal to the sample mean and variance of the historical data. The objective of considering these priors is to assess the impact of eliciting a prior distribution on the predictive accuracy of the model.

TABLE 1: Prior Parameters of the Beta Bayesian Kernel Models

Model	Prior Distribution	α	β
Beta Bayesian Kernel I	Uniform	1	1
Beta Bayesian Kernel II	Jeffrey's	0.5	0.5
Beta Bayesian Kernel III	Empirical	1	$1/(1+\bar{X})$

The predictive accuracy metrics are used to assess the ability of the model to correctly classify new data points given their attribute information. Since the outcome of the model is a probability distribution of the parameter of interest, we will use a point estimate which is the average of the posterior distribution, Eq. (6). If the estimate is above 0.5, the point is positively classified indicating that a supply chain disruption will most likely occur. If the estimate is below 0.5, the data point would belong to the negative class.

$$\bar{\theta}_i = \frac{\alpha^*}{\alpha^* + \beta^*} \tag{6}$$

Error! Reference source not found. is a summary of predictive accuracy metrics, the ability to correctly classify a data point in the positive class (true positive rate, TP), the ability to correctly classify a data point in the negative class (true negative rate, TN), and the accuracy score, $ACC = \sqrt{TP \times TN}$. These accuracy metrics were computed for the weighted Bayesian kernel model under the three assumptions for the prior distribution from Table 1. A cross-validation technique is used to compute the metrics in **Error! Reference source not found.**, whereby 70% of the data is used to train the model and the model is tested on the remaining 30% of the data.

The predictive accuracy of the Bayesian kernel model is compared to more traditional statistical techniques for binary data such as classification trees and generalized linear models, in particular the logistic regression. A classification tree is a non-parametric technique that is built based on a tree-like structure where intermediate nodes represent a single attribute and the edges stemming from such nodes are predicates on that attribute. The leaf nodes at the end of the tree correspond to a particular class for which the values are used for prediction. Classification trees are easy to interpret, however, they are less powerful predictive tools than parametric methods such as generalized linear models. We also compare the Bayesian kernel model to a logistic regression model which assumes that the outcome variable follows a binomial distribution and computes the logit of the probability of success which is our parameter of interest, θ_i, as a linear function of the attributes, Eq. (7)

$$logit(\theta_i) = \beta_0 + \beta_1 x_1 + \cdots \beta_d x_d \tag{7}$$

The cross validation technique was applied to all the models and the predictive accuracy metrics were computed across 100 iterations. The results summarized in Table 2 represent the average of the metrics over all the iterations.

The Beta Bayesian kernel model provides the best (and similar) overall accuracy with a uniform and a Jeffrey's prior distribution, followed by the classification tree. The lowest accuracy was provided by the logistic regression and the Beta Bayesian kernel model that had an empirical prior distribution. In addition to that, these two models provide the highest rate of accurately classifying new data points in the positive class compromised by a much lower true negative rate in comparison to the Beta Bayesian Kernel I and II models and the classification tree denoting an overestimation of the probability of a supply chain disruption. This suggests that the logistic regression was not capable of accounting for the imbalance in the data whereby the results are heavily dependent on the historical data. The Beta Bayesian Kernel III model shows a similar behavior in which the effect of the weight ratios is masked by the empirical prior parameters that are shaping the distribution of the probability of a disruption according to the imbalanced historical data. The Beta Bayesian kernel models with the weak priors provided the best true negative rate.

TABLE 2: Predictive Accuracy Metrics

Model	True Positive Rate	True Negative Rate	Accuracy Score
Beta Bayesian Kernel I	0.82	**0.74**	**0.77**
Beta Bayesian Kernel II	0.82	**0.74**	**0.77**
Beta Bayesian Kernel III	**0.96**	0.46	0.64
Logistic Regression	0.95	0.43	0.64
Classification Tree	0.92	0.6	0.74

According to the predictive accuracy analysis and judging from the overall accuracy, we can conclude that the Beta Bayesian kernel model with weak priors performs better than the model with a strong empirical prior. Traditional parametric statistical techniques such as the logistic regression overestimated the positive class while non-parametric techniques such as the classification tree had more similar results to the best Beta Bayesian kernel models, although the negative class was underestimated. For the purpose of risk management strategies in multinational companies, an overestimation of the likelihood of a disruption might result in costly and unnecessary preparedness investments which are often not preferred by risk managers. On the other hand, an underestimation of that probability may lead to large unexpected losses in the case of a disruptive event for which the company was not prepared. An underestimation of the negative class can be misleading in identifying circumstances and factors that might lead to a global supply chain disruption, this can especially be impactful on companies with a risk averse management.

V.B. Significance of attributes

As mentioned earlier, the data contains 42 attributes that may have an impact on the probability of a global supply chain disruption. In the predictive accuracy analysis conducted above, we included all the attributes in the models. As such, we did not account for the significance of these attributes and did not consider their true impact on the outcome variable.

In this section, we revisit the logistic regression, and, using the stepwise regression method, we identify the regression model that best fit the data and that contains the most important variables. The method is commonly used in high dimensional data sets and is effective as a variable selection technique. A stepwise regression method would fit multiple models, successively adding and removing variables, and select a subset of attributes that provide the best fit for the regression model. The resulting subset of variables are considered to be the most significant and impactful on the outcome variable, and they are summarized in Table 3.

TABLE 3: Significant Attributes

Question number	Attribute
Q6	Supply Chain partners in risky areas
Q9	Supply continuity plan under significant disruption
Q15c	Informal procedures for threat assessment to Supply Chain resilience
Q17f	Spending on business disruption insurance
Q18	Consideration of safety stock and inventory cushion
Q20a	Lack of buy-in from senior executives
Q20e	Poor visibility into suppliers' risk factors

According to the preliminary summary statistics done in section IV, out of the companies that experienced a disruptive event, 62% have key supply chain partners in areas of the world that are considered risky with exposure to natural disasters, extreme weather, and/or political turmoil. As suspected, the location of the key supply chain partners in risky areas is among the most impactful attributes. The rest of the significant attributes are all related to the risk management procedures and strategies of the company, such as expenditures on insurance, continuity plans, and other preparedness measures. Surprisingly, the industry type and size of the company did not show up among the most significant variables, further analysis would determine the reason of that outcome.

VI. CONCLUDING REMARKS

This work deployed probabilistic and data-driven techniques to study the risk analysis of global supply chains. The goal of the research was to predict the probability of a global supply chain disruption given information on past disruptions, the company's characteristics, its suppliers, and its risk management strategies. The data was provided by the American Productivity and Quality Center who conducted a survey for 196 companies, collecting data in the form of 42 attributes covering different aspects of supply chains risk management in addition to the companies' characteristics. The majority of the companies had experienced a supply chain disruption in the past, making the data heavily imbalanced. We proposed to deploy a Beta Bayesian kernel model to predict the likelihood of a disruption. The model integrates the Bayesian property which accounts for the uncertainty and any prior knowledge with the kernel function which captures the non-linear relationship between the attributes. Several prior distributions were considered for the Bayesian model to account for multiple levels of knowledge and the models were compared to non-Bayesian statistical techniques, the logistic regression and the classification tree. Overall, the Beta Bayesian kernel model performed better with a weak prior distribution. The logistic regression and the Beta Bayesian kernel model with the empirical prior were heavily influenced by the imbalance in the data and resulted in an underestimation of the negative class. Finally, a stepwise regression method was used to determine the most significant attributes which included the location of key supply chain partners as well as procedures for supplier risk assessment and expenditures on safety stock and insurance.

Future work will compare the statistical models given different subsets of the significant attributes as well as additional statistical modeling to further validate the results in this research and investigate the absence of the industry type and the size of the company from the most significant variables.

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