Generating Correlated Catastrophic Disruption and Yield Loss Logistics Risks with Known Expected Value and Variance-Covariance Structure

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Abstract. We develop procedures that generate correlated catastrophic and yield loss logistics risks. Specifically, our procedures can easily generate random occurrence of the logistic losses for suppliers, who are subjected to both correlated catastrophic disruptions, i.e. correlated binary variables, and uncorrelated yield loss, i.e. truncated distributions. The exogenous inputs for the correlated catastrophic loss are the expected values and covariance matrix of the correlated disruption events. We introduce a simple algorithm for generating two and three correlated binary variables. A method to extend our correlated binary variable generating procedure to higher-dimensional case is also discussed. For yield loss, our algorithm uses the observed effective mean and variance from a data set, the truncation limits and the distribution generating the yield loss or effective yield. Our algorithm calculates the parameters for the truncated distributions with given effective mean and variance. This allows the practitioners to compare the simulation results for logistics yield loss across several distributions, while keeping the effective mean and variance consistent.

Keywords: logistic risks, truncated distribution, correlated binary variable, heuristic algorithm

1. INTRODUCTION

In recent decades, firms have experience substantial shifts in globalization and new technology evolution. International manufactures such as Toyota, Samsung and Apple have supply chains that span continents. Unfortunately, globalization and new technology not only bring the profit to the firm, they can also introduce risks to the firm's supply chains (Craighead, 2007; Helbing 2013), which create challenges in the management of their spreading supply chains. The logistics risk is one of the supply chain risks that is an inherent and growing part of the transportation process. The primary concern is how to monitor, evaluate and possibly re-configure logistics risks in the supply chain based on a risk-benefit trade off. This issue has become an important concern for globalized firms.

Logistics risks can be categorized into two components: yield loss and catastrophic loss. In yield loss, logistics risk is a proportional loss caused by random events during shipping and handling. Whereas, catastrophic loss can be caused by natural disasters such as eastern Japan earthquake in 2011, or manmade disasters such as piracy in Africa, and the China milk powder scandals in 2008 and 2010 (Yuasa and Foster, 2011, ISS, 2013,). Sometimes a political event can also cause production breakdowns, e.g. the Arab spring uprising (Helbing, 2013). In the case of the eastern Japan earthquake, Toyota experienced a worldwide production shutdown. In the case of the China milk powder scandal, many Taiwanese food manufacturers were forced to recall and destroy their products that contained the Chinese milk powder (USA Today, 2008). All these events impact not just the production location, but also spread more broadly and may have a greater impact on the supply chain than anyone might have predicted.

While random yield loss might primarily depend on a supplier's ability to manage their logistics, catastrophic loss might be dependent both on both the supplier and a secondary factor (e.g., Chinese milk powder scandal or the Arab spring uprising). Catastrophic loss of this nature represents a major disturbance in the supply chain that is best represented by a single perturbation. Random perturbations of this nature behave like Bernoulli random variables. Random yield loss and catastrophic loss should both be considered in the supplier's risk management strategy. To address the need of easily generating both logistics risks, we first need to be able to generate correlated binary random variables that can represent the catastrophic risks and also be able generate the yield loss from distributions that are truncated at zero and one.

In this project we assume firms have historical data or managerial insights concerning the expected probability for catastrophic loss events, the covariance matrix associated with these catastrophic losses, and the mean, variance and type of the distribution of the random yield loss. For the catastrophic losses, a method allowing for an unstructured form of the covariance matrix is developed. However, not all solutions are feasible given the specified mean vector and covariance matrix. In addition, the method doesn't require the managers to estimate the parameters for yield loss distribution by truncated distribution estimation. Furthermore, constraints for the solution space of such distribution increase exponentially as the number of supplier increases. Thus, the chance of a given mean vector and covariance structure producing a feasible solution is very unlikely when dimensionality exceeds three (e.g., the number of supplier exceeds three).

Instead of pursuing a method that generates high-dimensional correlated-binary random variables, development focused on a method that can generate correlated binary random variables up to dimension 3, while preserving the specified mean vector and covariance matrix. The method developed is simple to implement and, unlike the other approximate method, it preserves the exact covariance structure, if such distribution exists. We also briefly discuss how to extend our method to the high-dimensional binary distribution.

For the logistics yield loss, a procedure is developed to generate the random yield loss based on several commonly used distributions, namely, the normal, lognormal, gamma and Weibull. In order to get the proper yield loss, which is between zero and one, we have to use the corresponding truncated distributions. A simple algorithm is proposed to convert the observed mean and variance to the parameter for a specific distribution. The algorithm generating the truncated distribution is abounded, (see Nadarajah and Kotz, 2006), however, up to best of our knowledge, a simple method that can calculate the parameters of the truncated distribution based on mean and variance of the real data is not well addressed.

The proposed algorithm can serve as a simulation method for comparison risk management alternatives. In many cases, risk managers have some idea about the underlying yield loss distribution but cannot be certain of the true underlying distribution. By implementing the proposed algorithm, simulation results for different forms of logistics yield loss can help risk managers better understand the consequences associated with logistics risks. In fact, if we specified the yield loss distribution and solve its parameters with respect to the observed mean and variance, we might or might not able to find a reasonable solution. This fact can also help the manager to examine their presumptions. For example, we found that the normal distribution might not be a good underlying assumption when the yield loss has a fat tile. After both of the catastrophic and yield losses are generated, we can use the data set to numerically evaluate a given supply chain risk management model. Since our model is rather simple the solution time is fairly short, we can use this simple method to conduct an extensive sensitivity analysis.

The remainder of this project is structured as follows: Section 2 reviews the relevant literature. Section 3 introduces the modeling framework for both catastrophic loss and the yield loss. Section 3 provides the details of the algorithm for implementation of correlated binary variables. Section 4 summarized simulation results for both logistics disruptions and yield loss risks based on given value of effective mean and variance-covariance structures. Section 5 summarize the results of this study.

2. LITERATURE REVIEW

While the logistics risks are a well-studied topic in the area of supply chain risk management, there need for the implementation side of the problem. Simulation models and sensitivity analysis are powerful tools for risk management, but users face the problem of how to construct high quality input data for logistics risks. In this project we try to address this question by proposing a solution method that can generate both correlated catastrophic yield loss and independent yield losses.

There are two major approaches to randomly generating correlated binary variables. The first approach is to generate the variables with a specific correlation structure, while the second is to use another distribution to approximate the correlation structure of the binary variables. Lee (1993), addresses both approaches are but does not consider the covariance structure. Emrich and Piedmonte (1991) propose a method that uses a multivariate continuous distribution to approximate the correlated binary distribution. While their method explicitly considers both mean vector and covariance structure of the variables, the solution doesn't preserve the exact covariance structure. Lunn and Davies (1998) provide a simple algorithm that can be applied to some special forms of the covariance matrix. However, their method cannot handle negatively correlated binary variables. Oman and Zucker (2001) introduce a simple method to generate correlated binary variables that have a specific type of covariance structure, namely AR(1), MA (1) and intraclass correlation. However, their method only applies when all the element of covariance matrix is positive. Oman (2009) extended Oman and Zucker's (2001) work by modified the algorithm so that it can generate the negatively correlated binary variables. However, Oman (2009) has two drawbacks, first the focus remains on AR(1), MA (1) and intraclass correlation covariance matrices and second, the range of feasible correlation values are restrictive and decreases as the number of random variables increases.

A major drawback to the generation of any correlated binary random variables with dimensions greater than two is that one cannot guarantee that the correlation structure is maintained. Chaganty and Joe (2006) studied the necessary and sufficient conditions for the existence of a multivariate binary distribution for a given the mean vector and correlation structure. They also compare their method, the three methods already discussed and the method introduced by Emrich and Piedmonte (1991), Qaqish (2003), and Park et al. (1996). Park et al (1996) propose an algorithm that to generate the correlated binary variables when the variables are positively correlated. Unlike Park et al (1996), Qaqish's (2003) method can generate correlated binary random variables with unequal means and negative correlated binary variables. However, the method doesn't allow high correlation (e.g., correlation > 0.55), even in the relatively simple 3-dimensional case. The same observation can be found in Chaganty and Joe (2004). The authors also stats that when the number of binary variables increases, the solution space of feasible covariance matrices gradually decreases. Thus, for many, if not most cases, the generation of correlated binary random variables is not feasible.

In the other hand, the logistics yield loss due to careless handling, demand resulting from the switch between transportation methods or other causes are independent in natural. In addition to the independency, the logistics yield loss has lower and upper limits, zero and one, respectively. Many of researchers has develop a truncated distribution to generate the random value for normal, lognormal, gamma, and Weibull, but the parameters of original distribution is required (Philippe,1997; Craighead, 2007). We can also estimate the parameters from the data if we know the underlying distribution. (see Chapman, 1953; Amemiya, 1973; Jawitz, 2004)

We have note that the proper truncation is very important in the simulation study. Fu and Noche (2012) study how the truncation of logistics yield distribution influences the final result of a shipment consolidation model. Savenkov (2009) also demonstrate the importance of properly truncated distribution to a simulation of Wind or Wave energy capacity. They choose to model the logistics yield loss with the Weibull distribution. They find that even the simulated data from truncated and un-truncated Weibull are not very different for the first glance. The resulting shipment consolidation decision is very different between these two distributions. Thus, for the distributions that are studied by the pervious literature in the area of logistics yield loss we develop the explicit procedure (Yano and Lee 1995; Tomlin 2006).

To develop a simple algorithm that takes effective mean and variance and search for the parameter(s) for a specific distribution, we need to derive the equation for first two moments for the truncated. After we obtain the first two moments we can solve 2-variable system non-linear equations for parameters. There are various researches have study the moments for the truncated distribution. This type of moments also referred as incomplete moments or partial moments. The early work of partial moments study can be date back to Winkler et al. (1972). The authors derive the partial moments for the Pearson family, i.e. beta, gamma, chi-square, normal, and student t. More recently, Philippe (1997) study the right and left truncated gamma and find when the upper limit is exactly 1, the truncated distribution can be rewrite as a mixture of beta distribution. The author introduces some useful insight of how to efficiently generate this type of right truncated gamma distribution but doesn't study the relationship between the effective mean and variance and un-truncated distribution's mean and variance. In this project, our solutions mainly following the incomplete movements that are derived by Jawitz (2004). Jawitz (2004) derives the incomplete moment for normal, tree-parameter lognormal, lognormal, and Weibull.

This study,

(1) creates a simple algorithm to generate the correlated binary variables.

(2) provides a simple algorithm that takes effective mean and variance and generate the random variables from specified distribution.

(3) discusses when and why to use our algorithm or other algorithms.

(4) gives a general guideline of implement the different yield loss distribution by effective mean and variance.

3. MODEL FORMULATIONS

In this section, we formulate the model for the correlated disruption risks and the logistics yield loss distributions. For the correlated binary variables, there are a set of constraints that associate with the feasible solution for a given covariance structure. We explicitly state these constrains and propose a solution algorithm to find the necessary parameters for generating occurrence of disruptions. For the logistics yield loss, we derived the explicit formula to convert the effective mean and variance to the parameters in truncated distributions. A solution algorithm is proposed in the end of the section.

3.1 Correlated Binary Variables

The method proposed for the generation of correlated binary observations is based on the solution to a system of linear equations, but is limited to a dimension of at most three binary random variables. Let denote an n dimensional row vector of possible binary outcomes and denote the probability of event. In the case of n = 2, can take on the possible outcomes of {(1,1), (1,0), (0,1) and (0,0)}, where 1 denotes success and 0 denotes failure. Generating correlated binary data requires knowledge of the outcome probabilities. Computing the outcome probabilities requires knowledge of the desired proportions for each of the random variables, along with the associated the covariance structure between the random variables. The number of possible outcomes for an n dimensional binary row vector is 2n. Thus, as the number of correlated binary variables increases, the number of possible outcome and associated probabilities increases exponentially. To determine the outcome probabilities requires solving a system of n(n + 1)/2 linear equations, along with the condition that the sum of the outcome probabilities sum to 1.0. These equations consist of relating the desired proportions and covariance for the binary variables to the outcome proportions (n and n(n – 1)/ 2 equations, respectively). However, this approach does not guarantee that the solution of the linear system is unique.

3.1.1 Generating 2-Dimensional Correlated Binary Variables

Letting π denote the desired mean vector and the Σ desired covariance structure, then for n = 2 binary variables the following relationships between the desired mean and covariance structures and the outcome probabilities are easily established:

$$Y = \begin{bmatrix} 00 \\ 10 \\ 01 \\ 11 \end{bmatrix},\ P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix},\ \text{and } E[Y] = \pi = [\pi_1 \quad \pi_2] = Y'P \quad (3)$$

The covariance matrix of the binary variables is the following:

$$\Sigma = Y'D_pY - (Y'P)(Y'P)' = Y'D_pY - \pi'\pi \quad (4)$$

$$Y'D_pY' = \Sigma + \pi'\pi \quad (5)$$

By definition $\sigma_i^2 = \pi_i(1-\pi_i)$, thus there is no need to specify the variance associated with each binary random variable. The system of equations needed to solve for the outcome probabilities is:

$$\pi_1 = P_4 + P_2 \quad (6)$$

$$\pi_2 = P_4 + P_3 \quad (7)$$

$$P_4 = \pi_1\pi_2 + \sigma_{12} \quad (8)$$

$$P_1 + P_2 + P_3 + P_4 = 1 \quad (9)$$

Given (π, Σ), the a unique solution for the outcome probabilities is

$$P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} = \begin{bmatrix} 1 - P_1 - P_2 - P_3 \\ \pi_1(1-\pi_2) - \sigma_{12} \\ \pi_2(1-\pi_3) - \sigma_{12} \\ \sigma_{12} + \pi_1\pi_2 \end{bmatrix} \quad (10)$$

subject to $P_1, P_2, P_3, P_4 \geq 0$.

Using the linear system defined above, the P_i s can be solve for as a function of the inputs. To increase the speed solution of the algorithm it is suggested to first check for existence the desired set of binary variables by using the conditions derived by Joe (1997):

$$\text{L}=\frac{1}{2}\left[-(\pi_1\pi_2)-(1-\pi_1)(1-\pi_2)+\left|(1-\pi_1)(1-\pi_2)-\pi_1\pi_2\right|\right] \leq \sigma_{12} \quad (1)$$

$$\text{U}=\frac{1}{2}\left[\pi_2(1-\pi_1)\right]+\left[\pi_1(1-\pi_2)\right]-\frac{1}{2}\left|\pi_2(1-\pi_1)-\pi_1(1-\pi_2)\right| \geq \sigma_{12} \quad (2)$$

If the desired set of binary variables exists and the vector of outcomes, *P*, is determined from the system of equations, then the following algorithm can be used to generate the binary variables:

1. Generate a random number from U ~ Uniform [0,1]
2. If $U \leq P_1$, let the resulting event be Y_1
   Else if $P_1 \leq U \leq P_1 + P_2$, let the resulting event be Y_2
   Else if $P_1 + P_2 \leq U \leq P_1 + P_2 + P_3$, let the resulting event be Y_3
   Else let the resulting event to be Y_4
3. Repeat 1 and 2 until desired number of binary vectors are generated.

So long as the conditions defined by Joe (1997) are met, the P_i s can be computed, and subsequently the binary variables with required covariance structure can be generated.

3.1.2 Generating 3-Dimensional Correlated Binary Variables

The outcome matrix, Y, the outcome probabilities and the relationship between the desired binomial proportions for the three dimensional case are:

$$Y = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix},\ P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \\ P_7 \\ P_8 \end{bmatrix},\ \text{and } E[Y] = \pi = [\pi_1 \quad \pi_2 \quad \pi_3] = Y'P \quad (11)$$

In addition, the relationship between the desired covariance matrix and the outcome matrix and outcome probabilities are given by $Y'D_pY' = \Sigma + \pi'\pi$. The linear equations are obtained from these relationships:

$$\pi_1 = P_2 + P_5 + P_6 + P_8 \quad (12)$$

$$\pi_2 = P_3 + P_5 + P_7 + P_8 \quad (13)$$

$$\pi_3 = P_4 + P_6 + P_7 + P_8 \quad (14)$$

$$P_5 + P_8 = \pi_1\pi_2 + \sigma_{12} \quad (15)$$

$$P_6 + P_8 = \pi_1\pi_3 + \sigma_{13} \quad (16)$$

$$P_7 + P_8 = \pi_2\pi_3 + \sigma_{23} \quad (17)$$

$$P_1 + P_2 + P_3 + P_4 + P_5 + P_6 + P_7 + P_8 = 1 \quad (18)$$

A unique solution for the Ps does not exist, but can be solved with respect to P_8, and result in the following:

$$P_1 = \pi_1\pi_2 - \pi_1 - \pi_2 + \sigma_{12} - \pi_3 + \sigma_{13} + \pi_1\pi_3 + \sigma_{23} + \pi_2\pi_3 + 1 - P_8 \quad (19)$$

$$P_2 = \pi_1 - \sigma_{12} - \pi_1\pi_2 - \sigma_{13} - \pi_1\pi_3 + P_8 \quad (20)$$

$$P_3 = \pi_2 - \sigma_{12} - \pi_1\pi_2 - \sigma_{23} - \pi_2\pi_3 + P_8 \quad (21)$$

$$P_4 = \pi_3 - \sigma_{13} - \pi_1\pi_3 - \sigma_{23} - \pi_2\pi_3 + P_8 \quad (22)$$

$$P_5 = \sigma_{12} + \pi_1\pi_2 - P_8 \quad (23)$$

$$P_6 = \sigma_{13} + \pi_1\pi_3 - P_8 \quad (24)$$

$$P_7 = \sigma_{23} + \pi_2\pi_3 - P_8 \quad (25)$$

The solution must satisfy the above constraints, which are functions of the covariance matrix and expected value vector. We note that all constrains are linear, thus the solution space is a convex hull. This implies that even though the solution space is decreasing the system equations can still be solved optimally.

$$P_5 + P_8 \geq \pi_1 + \pi_2 - 1 \quad (26)$$

$$P_7 + P_8 \geq \pi_2 + \pi_3 - 1 \quad (27)$$

$$P_5 + P_8 \leq \frac{1}{2}\left(\pi_1 + \pi_2 - \left|\pi_1 - \pi_2\right|\right) \quad (28)$$

$$P_7 + P_8 \leq \frac{1}{2}\left(\pi_2 + \pi_3 - \left|\pi_2 - \pi_3\right|\right) \quad (29)$$

$$P_8 \leq \frac{1}{2}\left(\sigma_{12} + \pi_1\pi_2 + \sigma_{23} + \pi_2\pi_3 - \left|\sigma_{12} + \pi_1\pi_2 - \sigma_{23} - \pi_2\pi_3\right|\right) \quad (30)$$

$$P_8 \geq \left(\sigma_{12} + \pi_1\pi_2 + \sigma_{23} + \pi_2\pi_3 - \pi_2\right) \quad (31)$$

$$P_6 \geq \pi_1 + \pi_2 + \pi_3 - 1 - \sigma_{12} - \pi_1\pi_2 - \sigma_{23} - \pi_2\pi_3 \quad (32)$$

$$P_6 \leq \frac{1}{2}\left(\pi_1 + \pi_3 - \sigma_{12} - \pi_1\pi_2 - \sigma_{23} - \pi_2\pi_3 - \left|\pi_1 - \pi_3 - \sigma_{12} - \pi_1\pi_2 + \sigma_{23} + \pi_2\pi_3\right|\right) \quad (33)$$

$$0 \leq P_i \quad (34)$$

As can observed from the above equations the solution to the linear system of equations is not unique. From a practical point of view, we can set the probability of all binary variable to be positive, and one of the probability to be zero. We propose the user to solve the system equations using linear programming while minimizing P_8.

As stated in Chaganty and Joe (2006), the n-dimensional binary distribution has inequalities on its solutions spaces. However, due to the fact that the number of constraints are increasing exponentially in number of variables, the solution rarely exists. Furthermore, even when the solution exists, only one pair of binary variables are significantly correlated, i.e. covariance greater than 0.1, while others are almost uncorrelated. Thus, we believe 3-dimensional binary distribution should be a practical and realistic subgroup size. For generating the correlated binary variables for dimensions of more than 3 we purpose a two-tier solution procedure. We suggest the risk managers conduct a simple clustering study or discrimination method to form subgroups within the supplier base. Then do the pair-wise correlated binary variable or tri-variate binary variable.

3.2 Logistic Yield Loss Distributions

In this section we introduce a way to generate logistics yield loss from a distribution that has support [0, 1]. Therefore, we have to develop a method to generate a random yield loss from a truncated distribution when only the effective mean and variance are given. We denote the truncation limits as an interval [a, b]. The default value of the truncation limits are [0, 1]. If the distribution has a feasible support, we also derive the effective mean and variance with right truncated distribution.

In this project we use the partial moments derived by Ja witz (2004), and generate the yield loss with the R-package that developed by Nadarajah and Kotz (2006). The yield loss distribution is usually left skewed and has significa nt probability of a large loss. Thus, we recommend checking t he kurtosis of the yield loss from observed data before solve f or the parameters. In a numerical study we find that with a gi ven mean and variance, either a unique solution is found, or n o solution exists. The system of non-linear equations presented in Table 2 can be solved by R-package "nleqlv" developed by Haaselman (2014). For Matla b, the nonlinear system equation can be solved by "fsovle" an d the truncated distribution can be generate by the following procedure: (1) set pd = makedist ('name of distribution'), (2) set t = truncated(pd, lower limit, upper limit), and (3) r = rand om(t, number of rows, number of columns). Due to the spa ce constrain the explicit truncated mean and variance for each distribution used in the simulation design are avail able upon request to authors.

3.2.1 Simulation Procedure

It is worth pointing out a few cautions in the implementation of the algorithm: (i) not every pair of effective mean and variance has a solution. (ii) The solution found by our function might not be unique, (iii) Normal distribution is not a very good distribution for the truncated logistics yield distribution, especially when these distributions represent the proportion of the actual receipts. (iv) Since the logistics yield loss is a left skewed distribution, for some naturally right skewed distributions such as gamma, lognormal, the effective mean shall be set at 1-(expected defect). That is the logistics effective yield in stand of yield loss should be generated. Now we provide a brief algorithm and code for both Matlab and R.

Simulation Algorithm:

Step 1: Input type of distribution, number of trials needed, the effective mean and variance as well as the truncation interval [a, b].

Step 2: Check the skewness, if the data is left skewed set effective mean = 1- observed mean, otherwise set effective mean = observed mean. Set the effective variance = observed variance.

Step 3: Use the effective mean and variance to solve for the parameters in un-truncated distribution. If the solution exist, set the solution as the starting point. If the solution doesn't exist set the initial solution as [1, 1].

Step 4: Solve the non-linear system equations given in Table 2 with "fsolve" in Matlab or package "nleqslv" in R.

Step 5: If the solution exists but not unique pick the one with the largest location parameter. If the solution doesn't exist go to step 6. Use the output solution to simulate the random yield loss for the specified distribution. Otherwise go to step 7.

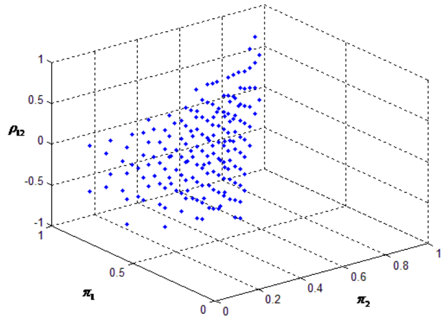
Step 6: Generate the random number from truncated distribution.

Step 7: Display ('Solution doesn't exist.').

4. NUMERICAL STUDY

4.1 Simulation Studies for Correlated 2- and 3-demantional Binary Variables

For the probabilities of the occurrence of each disruption, we define each of them to range from 0.1 to 0.9 in increments of size 0.1, and covariance ranges from –0.25 to 0.25 in increments of size of 0.05, excluding 0. We test 81×10 = 810 combinations of mean vector and covariance matrices. Among these, 229 resulted in feasible solutions. Table 1 presents the feasible solutions under the conditions defined.



Similarly, for the 3-demandtional case, we defined e-ach of three probabilities to range from 0.1 to 0.9 in increments of size 0.1, and covariance ranges from –0.25 to 0.25 in increments of size of 0.05, excluding 0. We try 129×84×50×50 combinations of π_is, σ_{ij}s, σ_{13} and P_8 that range from 0.00 to 0.25. The Figure 2 indicates the percentage of feasible solutions. As it shows, when the covariance between binary variables are small and the probability. The feasible solutions are clustering around the low covariance structure. This result is consistent with argument we made in section 3.1.2, the feasible variance and covariance structure for a set of correlated disruptions are not practical. Again for any correlated disruption risks that excess 3-demantional, we suggest the user to dissect the suppliers into several subgroups that consist of members less or equal to three.

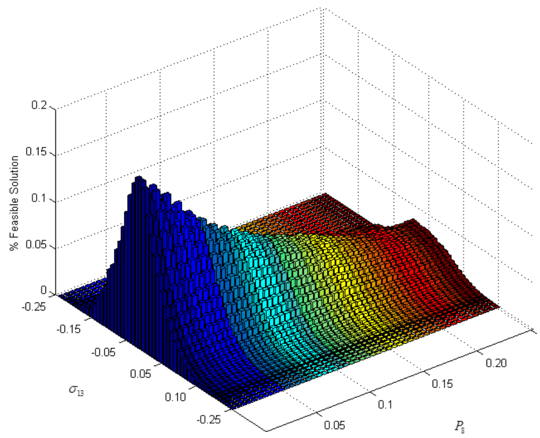


Figure 2: The plot for Percent Feasible Solutions in all Possible Simulation Trials

4.2 Simulation Study for Logistic Yield Loss

The simulation study for yield loss is conduct to demonstrate the proposed solution algorithm for converting effective mean and variance for the truncated distribution. While we drive all the exchange equations for the effective mean and variance for Normal, Lognormal, Gamma and Weibull with both one-tail and tow-trail truncated distributions, only the solution for two-tail truncated normal, one-tail lognormal and one-tail gamma are presented in the Table 1.

More specifically, all distributions are truncated at [0,1]. Even though we try all the combination of effective mean and variance for Weibull distribution, the solution for feasible mean and variance for truncated Weibull does not exist for these instance. It is worth noting that even though the expressions in Table 2 are not linear, the solution time using Matlab solver "fsolve" has never exceeded 1 minute.

Figure 1: The Plot of Expected Value for Each Catastrophic Event and Correlation of Events

Table 1: The Distribution Parameters According to the Effective Mean and Standard Deviation

Effective		**Truncated Normal**		**Truncated Gamma**		**Truncated Lognormal**		**Effective**		**Truncated Normal**		**Truncated Gamma**		**Truncated Lognormal**	
$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	μ	σ	κ	θ	m	s	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	μ	σ	κ	θ	m	s
0.75	**0.01**	0.75	0.01	604	0.00041	-0.672	-0.181	**0.8**	**0.01**	0.8	0.01	400	0.001	-0.778	-0.22
0.76	**0.02**	0.76	0.02	144	0.002	-0.667	-0.286	**0.8**	**0.02**	0.8	0.02	100	0.002	-0.748	-0.338
0.77	**0.03**	0.77	0.03	58.8	0.004	-0.659	-0.391	**0.8**	**0.03**	0.8	0.03	44.4	0.005	-0.717	-0.446
0.78	**0.04**	0.78	0.04	30.2	0.007	-0.648	-0.503	**0.8**	**0.04**	0.8	0.04	25	0.008	-0.684	-0.552
0.79	**0.05**	0.79	0.05	17.6	0.012	-0.634	-0.627	**0.8**	**0.05**	0.8	0.05	16	0.013	-0.65	-0.658
0.8	**0.06**	0.8	0.06	11.1	0.018	-0.616	-0.767	**0.8**	**0.06**	0.8	0.06	11.1	0.018	-0.616	-0.767
0.81	**0.07**	0.811	0.071	7.37	0.026	-0.594	-0.928	**0.8**	**0.07**	0.801	0.071	8.16	0.025	-0.581	-0.878
0.82	**0.08**	0.824	0.084	5.06	0.036	-0.569	-1.115	**0.8**	**0.08**	0.802	0.082	6.25	0.032	-0.546	-0.993
0.83	**0.09**	0.843	0.102	3.57	0.048	-0.539	-1.336	**0.8**	**0.09**	0.805	0.095	4.94	0.041	-0.511	-1.111
0.84	**0.1**	0.879	0.128	2.56	0.063	-0.505	-1.600	**0.8**	**0.1**	0.81	0.11	4	0.05	-0.477	-1.233
0.85	**0.11**	0.969	0.173	1.85	0.081	-0.465	-1.922	**0.8**	**0.11**	0.82	0.127	3.3	0.061	-0.442	-1.36
0.86	**0.12**	1.308	0.278	1.35	0.104	-0.421	-2.320	**0.8**	**0.12**	0.837	0.148	2.77	0.072	-0.408	-1.491
0.87	**0.13**	15.7	1.403	0.98	0.134	-0.371	-2.821	**0.8**	**0.13**	0.865	0.173	2.35	0.085	-0.374	-1.626
0.88	**0.14**	16.23	1.425	0.7	0.174	-0.314	-3.467	**0.8**	**0.14**	0.911	0.205	2.01	0.1	-0.341	-1.766
0.89	**0.15**	24.97	1.779	0.49	0.234	-0.252	-4.320	**0.8**	**0.15**	0.99	0.246	1.73	0.116	-0.308	-1.912
0.9	**0.16**	35.9	2.142	0.32	0.337	-0.183	-5.482	**0.8**	**0.16**	1.133	0.304	1.49	0.136	-0.276	-2.062

Unfortunately, with the effective means given in Table 1, we are not able to find a feasible solution for Weibull distribution. That shows, if the observed logistic yield loss is fitted by Weibull distribution by any statistical software, the best strategy is to use the other distribution to approximate it.

In the other side, a feasible solution might not be a reasonable solution. For example, the Gamma distribution with κ equals 604 and θ equals 0.00041 does not seems to be a rational choose for a logistic yield loss. The underlying distribution of that instance might be more likely to be normal.

5. CONCLUSION

Our approach to simulate the correlated catastrophic logistics risks is very simple and yields a solution range that is close to theoretical bounds. Our approach preserves the specified mean and covariance structure of the catastrophic loss, which is critical to the risk management. Our method is to use a more direct and simple method to explicitly model the variance and covariance structural of the correlated binary variables. In this project, we extend the model first proposed by Lee (1993) and add the conditions derived by Chaganty and Joe (2006). Our method with dimension less than three can take unequal variance and the wildest range of unstructured covariance matrix than the methods proposed by pervious literature (e.g. Emrich and Piedmonte, 1991; Park et al., 1996; Qaqish, 2003; Oman, 2009).

We also propose an algorithm that takes the mean and variance of the real data and numerically solve for the parameters for logistics yield loss distributions. This approach allow the user to compare the results simulated from different distributions without go through complicated parameter estimation. Our method is best fit when the underlying distribution is not clear to the user and the user desire to compare the decision under different distribution assumptions.

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