Assessing Supplier Default Risk on the Portfolio Level: A Method and Application

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Abstract

The main purpose of this paper is to quantify the risk in a buying firm's supplier portfolio that stems from the financial default of suppliers. Based on credit risk models we develop a methodology that buying firms can use to determine their exposure to supplier default risk. Empirical data pertaining to supplier portfolios of upper-class car models from three German automotive manufacturers is used to illustrate the application of the methodology. We show that some car models are exposed to higher risk. This places them at a disadvantage, because the higher the supplier default risk, the more likely it is that the supply of components can be disrupted and cars cannot be built and sold. Buying firms can use this methodology for the pro-active assessment of supplier default risk.

Keywords: Supplier default risk; Supplier portfolios; Credit risk models; Automotive industry

Introduction

Automotive manufacturers (original equipment manufacturers – OEMs) have faced a dramatic decline in sales and capacity utilization since the beginning of the economic downturn (Department of Commerce, 2009a). For many automotive OEMs their financial situation deteriorated substantially, while others even had to file for bankruptcy (e.g., Saab in February 2009; Chrysler in April 2009; GM in June 2009). The situation is even worse for automotive suppliers. Automotive manufacturers have been constantly seeking price concessions from their suppliers, while asking them to take on more design and manufacturing responsibilities and to absorb higher costs for their input materials. It is not surprising that this situation has placed many automotive suppliers under great economic pressure. As a result, the financial situation of many automotive suppliers has deteriorated (Department of Commerce, 2009b), and compared to previous years more and larger automotive suppliers have ended up, or are on the verge of ending up, in bankruptcy (e.g., Contech in February 2009; Visteon in May 2009).

In 2005, the Moody's rating of 54 global auto suppliers (from North America, Europe, and Asia) assigned investment-grade to only 33% of suppliers, but speculative-grade to 67%. The report's outlook was not much more promising: 11% of suppliers had a positive outlook, 59% a stable outlook, and 30% a negative outlook or were on review for possible downgrade (Murphy, Kelly, and Stoll, 2005). The situation has deteriorated since then. In 2009, from a total of 59 global auto suppliers only 24% maintained investment-grade while 76% were rated speculative. The outlook was also much worse: For 1% it was positive, for 34% it was stable, and for 65% it was negative (Harrod, 2009).

Supplier bankruptcies have become a major concern in the automotive industry. For automotive OEMs, the early identification of supplier default risk and the mitigation and management of supplier defaults have risen to the top of the agenda (Wagner, Bode and Koziol, 2009). The measures that OEMs take range from implementing early warning systems to changing sourcing strategies (e.g., from single to multiple sourcing) or financially supporting suppliers in order to keep the supply chain going (Milne, 2009). Such measures, however, can only be pro-actively implemented and effective if the OEM possesses a thorough understanding of the supplier default risk embedded in its supplier portfolios.

So far, the assessment and quantification of supplier default risk that goes beyond the analysis of supplier firm ratings (such as the ratings provided by Standard & Poor's, Moody's, or Fitch) has remained largely unexplored. Reasons are that the prediction of the behavior of firms that are connected in a supply network is complex and that supplier defaults are correlated and not independent events. Furthermore, firms do not have outright access to data for the assessment of supplier default risk. In consequence, there is a lack of quantitative models for the systematic quantification of supplier default risk.

Therefore, the first goal of this paper is to develop a method based on portfolio credit risk models that can be used to assess supplier default risk. Consistent with the extant literature that buying firms need to manage the risk in their supplier portfolio (as opposed to managing the risk of individual suppliers) (e.g., Choi and Krause, 2006; Wagner, 2004), the proposed method can be applied on the portfolio level. The second goal is to exemplify the application of the method by analyzing real-life supplier portfolios and assessing and comparing the default risk inherent in these portfolios.

The outline of the paper is as follows. Section 2 provides some background information on supplier portfolios and credit risk models. In section 3, we transfer the credit risk modeling approach to the purchasing context and provide a theoretical background on credit risk and supplier risk modeling. Next, we explain the methodology and how empirical data was obtained. In section 5, the results of the empirical analysis are presented. The paper provides discusses implications and concludes in section 6.

Background

Supplier portfolios

Markowitz (1952) proposed the portfolio concept for selection of investment opportunities. He argued that, due to a diversification effect, a collection of investment assets may have collectively lower risk than the sum of the individual asset. Since then, portfolio approaches have been used to represent risk and return trade-offs in making investment decisions. The portfolio approach has also been widely used in purchasing practice for classifying suppliers and materials based on various dimensions, such as purchasing volume, power-dependence relationships, or risk considerations (e.g., Bensaou, 1999; Gelderman and Semeijn, 2006; Kraljic, 1983). Wagner and Johnson (2004, p. 719) define a firm's supplier portfolio as "the set of supplier relationships assembled by the firm with the intent of managing risks and optimizing returns where management activities involve not just individual supplier relationships but the entire supplier portfolio as a group," pointing out that firms need to deal with risk in supplier portfolios beyond individual buyer-supplier relationships, that interdependencies among suppliers exist and that risk-return trade-offs need to be considered.

In the context of supplier defaults, a supplier portfolio perspective can also help firms in classifying suppliers and deriving groups of suppliers with low or high impacts in case of supplier default. In the following sections this portfolio perspective will be further used in the discussion of exposure, an important input variable of the credit risk models.

Credit risk models

In finance, various models for investment risk quantification and management have been developed. For example a bank determines the price of a loan mainly based on expected loss. The unexpected loss in a loan portfolio should be captured by economic capital, as Basel II regulation requires (Bluhm, Overbeck, and Wagner, 2003).

Figure 1 provides an overview of prominent credit risk models. For the purpose of this study, we adopt the CreditRisk+ model, which was initially developed by CreditSuisse First Boston in 1997, to model supplier default risk. First, it is a widely used and well accepted method for risk quantification. Second, in CreditRisk+ the risk driver is the default risk of the counterparties (obligors in banking) which suits well with the modeling of supplier defaults. Third, all the mathematical formulas in the model are documented and the technicalities are freely available (Wilde, 1997).

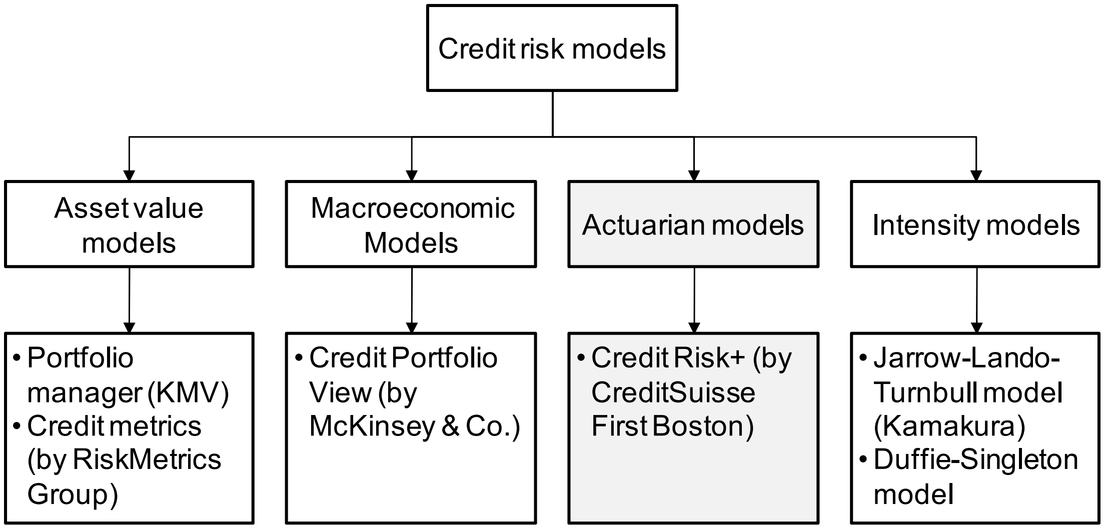


Figure 1. Overview of industry credit risk models (Bluhm et al., 2003)

Transferring Credit Risk Models to Supplier Portfolios

This section aims to provide an introduction to credit risk frameworks and to examine the applicability of these frameworks to the purchasing context. We first discuss the basic risk attributes of a counterparty (i.e., a supplier), including the default probability, the exposure, and the default correlation between counterparties. Second, we explain the Bernoulli model (Bluhm et al., 2003) as a basic approach of modeling defaults. Third, we introduce the CreditRisk+ model as an example of the industry credit risk model (Wilde, 1997).

Essential risk attributes of counterparties

Default probability. The default probability (DP) of a firm represents the probability that the firm goes into bankruptcy in a certain time period, typically one year (Bluhm et al., 2003).

Two approaches can typically be used to assign the DP to a firm. The first approach is *using market data of the firm to calculate the DP*. This approach is supported by previous research and finds its applications in various industry models. Altman (1968) shows the efficiency of predicting firm's bankruptcy by multiple discriminate models using financial ratios, for example liquidity ratio and leverage ratio. Jarrow and Turnbull (1995) propose a method of estimating default risk using the price of corporate bonds. In the well-known KMV credit risk model, the DP is defined in the content of an asset value process. The DP is the likelihood that the assets value of the firm becomes lower than the critical threshold in a certain period of time, usually one year (Bluhm et al., 2003).

The second approach is to *calculate the DP with ratings from rating agencies* like Moody's, Standard & Poor's, or Fitch. The rating agency measures the credit worthiness of a firm and assigns a rating to the firm which is expressed in a letter system. The transformation from the letter system of the rating to the DP can be done using historic default frequencies, for instance the Moody's historic bond default frequencies for Moody's ratings. Bluhm et al. (2003) suggest a three-step calibration method. The default volatility is also computed with this method.

1. For each letter rating class, compute the over-year mean value of the default frequencies and the standard deviation based on the yearly bond default data, such as the corporate default data from 1920 to 2006 by letter rating of Moody's (Hamilton, 2007).
2. Plot the mean value of the default frequencies of each class against the numbered rating classes for instance 1 (Aaa) to 7 (Caa-C). On a logarithmic scale the mean default frequencies can be fitted by a regression line. There is empirical evidence that default frequencies grow exponentially with decreasing creditworthiness. Hence an exponential fit is chosen to estimate the regression function.
3. Assign a DP using the regression equation from step 2.

In the first approach for obtaining DPs, collecting market data of the firm and modeling the DP has to be done by the researcher. In the second approach, the analysis of the firm is done by rating agencies. The advantage of the second approach is that it requires apparently less effort for data collection and analysis. One disadvantage of ratings is that rating agencies only rate a limited number of firms. For example worldwide only 59 automotive suppliers were rated by Moody's in the year 2009 (Harrod, 2009). For firms that are not rated, other methods such as peer-group analyses are required. Another disadvantage of ratings is that they are not transparent and may lead to misunderstanding. The ratings may not be reliable. For the purpose of this study we opted to use the second approach, by using the individual DPs of automotive suppliers from a rating evaluation.

Exposure at default. In banking the exposure at default (EAD) of an obligor contains two parts: drawn (OUTST) and undrawn loan (COMM) at the time before default (Bluhm et al., 2003), where

$$\mathrm{EAD} = \mathrm{OUTST} + \gamma * \mathrm{COMM} \tag{1}$$

and γ is the expected portion of the commitments likely to be drawn prior to default. An approach to determine "exposure at supplier default" would be to measure exposure as a dollar value. There are situations in purchasing where a dollar value of an exposure can be estimated. For example, in the raw material spot market the buyer can switch from a contracted supplier to a spot market to satisfy its demand. Haksöz and Kadam (2009) argue that in the setting above, the exposure at contract breach by a supplier is the difference between the spot market unit price and the contract unit price multiplied by the volume of the contract. However automotive parts, components, modules or systems are regularly customer-specific or even car model-specific, so that spot markets with price information do not exist. In case of a supplier default, the OEM cannot turn to the spot market and maybe just pay a higher price. The exposure at supplier default is an ex post measurement which is difficult to forecast accurately. However, OEMs might financially assess exposure (e.g., a simple way would be to use purchasing volumes for the components) and estimate and assign a dollar value for exposure to each supplier.

Besides the availability of such information, another difficulty is that supplier defaults are rare events and empirical reports of the loss from defaults are often not available. Nevertheless, one can identify determinants for defaults (e.g., complexity of the components, availability of suppliers, ease of switching suppliers) and derive a quantitative measure for exposure (on a scale other than dollar value), and use this information in the credit risk model.

Expected loss of single default. In the banking industry the expected loss of an obligor is measured in the following way: the bank assigns to a obligor denoted as i a default probability (DP), a exposure at default (EAD) and a loss fraction called the loss given default (LGD), describing the fraction of the exposure subject to be lost in the considered time period (Bluhm et al., 2003). The loss $\tilde{\mathrm{L}}$ of the obligor is defined by:

$$\tilde{\mathrm{L}}_{\mathrm{i}} = \mathrm{EAD}_{\mathrm{i}} * \mathrm{LGD}_{\mathrm{i}} * \mathrm{L}_{\mathrm{i}} \text{ with } \mathrm{L}_{\mathrm{i}} = 1_{\mathrm{D}}, \mathrm{P(D)} = \mathrm{DP}_{\mathrm{i}} \tag{2}$$

where D denotes the event that the obligor defaults in a certain period of time (most often one year). L_{i} is a Bernoulli random variable and $\mathrm{P(D)}$ denotes the probability of D. The expectation of any Bernoulli random variable 1_{D} is its event probability.

The expected loss (EL) of the obligor as the expectation of its corresponding loss variable $\tilde{\mathrm{L}}$ is determined by:

$$\mathrm{EL}_{\mathrm{i}} = \mathrm{E}[\tilde{\mathrm{L}}_{\mathrm{i}}] = \mathrm{EAD}_{\mathrm{i}} * \mathrm{LGD}_{\mathrm{i}} * \mathrm{P(D)} = \mathrm{EAD}_{\mathrm{i}} * \mathrm{LGD}_{\mathrm{i}} * \mathrm{DP}_{\mathrm{i}} \tag{3}$$

In this study the loss due to a supplier default for one OEM is similar to the obligor default in banking. The methods to calculate the loss in a credit risk model are already well established. The expected loss is also calculated according to equation (3).

Default correlation. Similar to the correlation between obligors in a loan portfolio, recent studies have shown that the defaults of suppliers in a portfolio can also be correlated (Babich, Burnetas, and Ritchken, 2007; Swinney and Netessine, 2009; Wagner, Bode and Koziol, 2009). Default correlation between firms in credit risk modeling should be the same from a bank and from an automotive OEM point of view. There are well established explanations about correlation in the credit risk modeling research, for instance the state of the overall economy or the situation in the particular industry.

Correlation modeling is an important and challenging part of credit risk modeling. One basic idea is to treat default probabilities as random variables (Bluhm et al., 2003). The default frequency of companies in the same rating class can vary from year to year. In the Bernoulli model the default correlations are fully captured by the covariance structure of the stochastic default probabilities. In the CreditRisk+ model the correlation is introduced by randomization of default intensity and sector analysis (Wilde, 1997).

Modeling of defaults: The Bernoulli model

The Bernoulli model is a basic model for modeling two state events. A supplier portfolio is a collection of a number of suppliers. The number of suppliers is denoted as m. In a two-state model, each supplier has two future scenarios: either the supplier defaults or the supplier survives. A variable L_i can be used to indicate these two states. In case that supplier i defaults, L_i equals to 1; when the supplier survives, L_i equals to 0. The default probability of supplier with indicator i is denoted as p_i. A vector of random variables $L = (L_1, \dots L_m)$ is called a Bernoulli loss statistics, if all marginal distributions of L are Bernoulli distributions:

$$L_i \sim B(1; p_i), \text{ i.e. } L_i = \begin{cases} 1 \text{ with probability } p_i \\ 0 \text{ with probability of 1-} p_i \end{cases} \tag{4}$$

The number of defaults in one portfolio is defined as

$$L = \sum_{i=1}^{m} L_i \, . \tag{5}$$

The easiest type of loss statistic can be obtained by assuming a uniform default probability p and independence between the suppliers. The mathematic form of this assumption is

$$L_i \sim B(1; p), \text{ and } (L_i)_{i=1,\dots,m} \text{ independent.} \tag{6}$$

In this case, the portfolio number of defaults L is a convolution of independent and identically distributed Bernoulli variables and therefore follows a binominal distribution with parameter m and p,

$L \sim B(m; p)$. The expected number of supplier defaults and the variance in one year are calculated with the following formulas:

$$E[L] = mp \text{ , and } V[L] = mp(1-p). \tag{7}$$

Keeping the assumption of independent suppliers, but allowing each supplier to have different default probabilities, the following expression is obtained:

$$L_i \sim B(1; p_i), \text{ and } (L_i)_{i=1,\dots,m} \text{ independent.} \tag{8}$$

The portfolio loss is still a convolution of the single loss variables. The first moment (the expected value) and the second moment (the variance) of the loss distribution L are:

$$E[L] = \sum_{i=1}^{m} p_i \text{ , and } V[L] = \sum_{i=1}^{m} p_i (1-p_i). \tag{9}$$

The assumption that the suppliers are independent in the default events is rather unrealistic. A basic idea for modeling correlated defaults is the randomization of the involved default probabilities in a correlated manner. This leads to so-called mixture models. In the *Bernoulli mixture model,* fixed default probabilities $p = (p_1, \dots, p_m)$ are considered as a realization of random default probabilities $P = (P_1, \dots, P_m)$. P follows some distribution function F with support in $[0,1]^m$. $L = (L_1, \dots, L_m)$ is a loss statistics vector with Bernoulli variables $L_i \sim B(1; P_i)$. The Bernoulli mixture model assumes that, conditional on a realization $p = (p_1, \dots, p_m)$ of P, the variables $L_1, \dots, L_m$ are independent:

$$L_i|_{P_i=p_i} \sim B(1; p_i), \ (L_i|_{P=p})_{i=1,\dots m} \text{ independent.} \tag{10}$$

The joint distribution of $L = (L_1, \dots, L_m)$ is determined by the following probability function:

$$P[L_1 = l_1, \dots, L_m = l_m] = \int_{[0;1]^m} \prod_{i=1}^{m} p_i^{l_i} (1-p_i)^{1-l_i} dF(p_{1,\dots,}p_m), \tag{11}$$

where $l_i \in \{0,1\}$. The expected value and variance of the single losses L_i are given by:

$$E[L_i] = E[P_i], V[L_i] = E[P_i](1 - E[P_i]) \text{ where } i = 1, \dots, m. \tag{12}$$

The default correlation in a Bernoulli mixture model is given by:

$$\mathrm{Corr}\left[L_i, L_j\right] = \frac{\mathrm{Cov}[P_i, P_j]}{\sqrt{E[P_i](1-E[P_i])}\sqrt{E[P_j](1-E[P_j])}} \tag{13}$$

For portfolios with a uniform default probability and a uniform correlation, equation (13) can be transferred to a default model with a Poisson distribution. P denotes the uniform random default probability. V[P] denotes the variance of P. $\overline{p}$ denotes the mean value of the random default probability P.

$$\mathrm{Corr}[\mathrm{L_i}, \mathrm{L_j}] = \frac{\mathrm{V[P]}}{\overline{\mathrm{p}}(1-\overline{\mathrm{p}})}. \tag{14}$$

For example, assume a portfolio has a uniform default probability of $\overline{p}$=3.558% and V[P] =0.002 (level of Moody's rating class B). Then, the correlation between any two counterparties is 0.064.

Modeling the portfolio loss distribution

Portfolio loss distribution. Portfolio loss distribution modeling is one step further than the modeling of portfolio default distribution. The severity of defaults, which are measured by exposures, may vary largely between suppliers. This is not captured in a portfolio default distribution. Thus, the portfolio loss distribution provides richer insights for credit risk management because all risk quantities, for instance the expected loss and the economic capital (Bluhm et al., 2003), are derived from this distribution. See Figure 2 for an illustration of a portfolio loss distribution. The control mechanisms of the losses at different levels are listed in Table 1. For a more detailed discussion of this topic we refer the interested reader to the technical documentation of CreditRisk+ (Wilde, 1997).

There are essentially two ways to generate a loss distribution: the Monte Carlo simulation and the analytical approximation. The main characteristics of these two methods, as well as the pros and cons are summarized in Table 2.

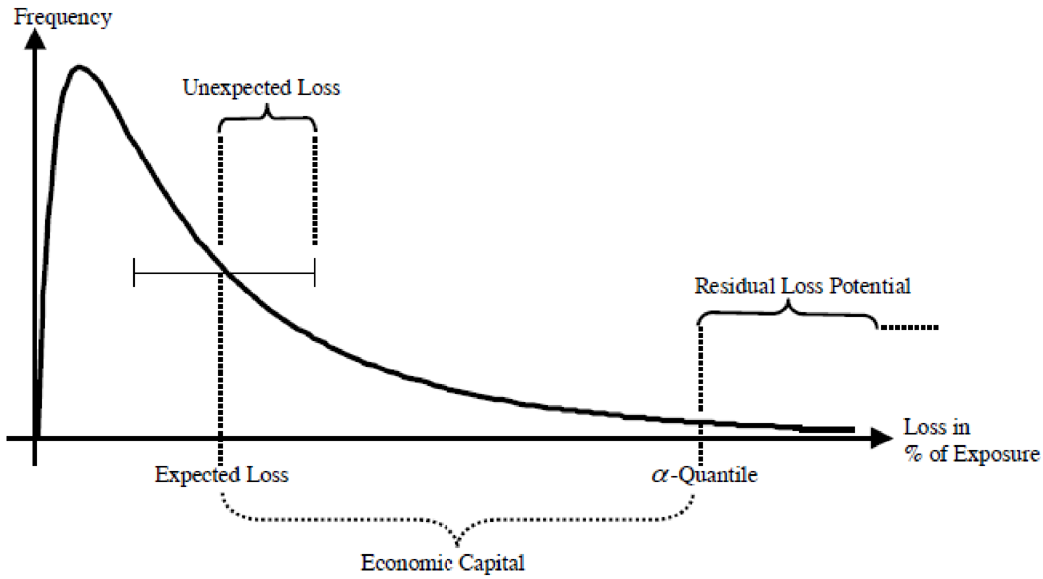


Figure 2. The portfolio loss distribution (Bluhm et al., 2003)

Table 1. Mechanisms for controlling the risk of credit default losses (Wilde, 1997)

Part of loss distribution	Control mechanism
Up to expected loss	Adequate pricing and provisioning
From expected loss to α-Quantile (for instance 99th percentile loss)	Economic capital and/or provisioning
Greater than the α-Quantile	Quantified using scenario analysis and controlled with concentration limits.

Table 2. Comparison of Monte Carlo simulation and analytical approximation method

	Monte Carlo Simulation	Analytical approximation
Generation of distri-bution of portfolio loss	N potential portfolio losses are simulated and tabulated in a histogram	Approximation by some closed form distribution, for example beta distribution using moment matching
Base of asset correlation modeling	Factor models, for example the Global Correlation Model from KMV	Practical experience with portfolios with known average asset correlation,
Default correlation form	Asset correlations between every two counterparties	An average correlation for all counterparties, for instance 20% for all corporate loans
Advantages	Accurately capturing the correlations inherent in the portfolio	Very little computation efforts
Disadvantages	Takes long time when the numbers of counterparties and the number of scenarios are large	Significant model risk from assumption of average asset correlation and approximation with known distributions

CreditRisk+ model follows a Poisson mixture approach. The concentration risk stemming from correlation between counterparties is measured using a sector analysis by introducing default rate volatilities. Sector analysis underlies the correlation structure between counterparties, which are influenced by the same underlying factor for instance the U.S. economy and the automotive industry. If two counterparties have no sector in common, there is no correlation between them. For the level of the correlation please refer to equation (138) of the technical documentation of CreditRisk+ (Wilde, 1997, p. 57).

Instead of modeling directly the portfolio loss distribution, CreditRisk+ model firstly derives the probability generation function of the portfolio loss (see equation (78) of the technical documentation of CreditRisk+ (Wilde, 1997, p. 48)). The loss probability is then solved by a recurrence function (see equation (77) and equation (80) of the technical documentation of CreditRisk+ (Wilde, 1997, p. 48-49)).

Risk contributions and pairwise correlations. Risk contributions and pairwise correlation are two measures connected with default loss distribution. Risk contribution measures the contribution of the counterparty to the unexpected loss of the portfolio, measured by a certain percentile level or the standard deviation. The sum of the risk contributions of all the suppliers in the portfolio should equal to the loss of chosen percentile (e.g., 99th percentile). Risk contributions of the suppliers have important implication in portfolio management. By removing counterparties with high risk contributions, the risk level can be decreased. See the technical document (Wilde, 1997) for an illustrative example.

The pairwise correlation function of two suppliers A and B are calculated with the following equation:

$$\rho_{AB} = (\mu_A \mu_B)^{1/2} \sum_{k=1}^{n} \theta_{Ak} \theta_{Bk} \left[\frac{\sigma_k}{\mu_k}\right]^2 \tag{15}$$

where k denotes the sectors with index k and n is the number of sectors. $\theta_{Ak}$and θ_{Bk} denote the sector decomposition of supplier A and B. μ_k denotes the long-term annual average number of defaults of sector k and σ_k denotes the standard deviation of number of defaults of sector k. μ_A and μ_B denotes the expected number of defaults of supplier A and B in a certain time period. When the considered time period is one year, μ_A and μ_B are equal to the default probability. If all the suppliers are allocated to a single sector, so $k = 1$, $\theta_{Ak} = \theta_{Bk} = 1$, the equation can be rewritten as:

$$\rho_{AB} = (\mu_A \mu_B)^{1/2} \left[\frac{\sigma_1}{\mu_1}\right]^2, \tag{16}$$

$$\sigma_1 = \sum_A \sigma_A \, , \mu_1 = \sum_A p_A \tag{17}$$

where p_A denotes the mean default probability of supplier A; μ_1 denotes the long-term annual average number of defaults of the single sector 1 and it equals to the portfolio sum of default probabilities; σ_A denotes the standard deviation of default probability of supplier A; σ_1 denotes the standard deviation of default probability. Because the fraction $\frac{\sigma_1}{\mu_1}$ is usually close to 1, the pairwise correlation has the same order as the term $(\mu_A \mu_B)^{1/2}$.

Method and Empirical Data

Empirical setting

We have chosen the German automotive industry for our empirical analysis for various reasons. It is a well known and important industry in many countries, particularly in Germany. Also, automotive OEMs are highly dependent on their suppliers. On the one hand, automotive OEMs are large and powerful customers, on the other hand, suppliers are critical for automotive OEMs to achieve and sustain competitive advantage due to the high degree of outsourcing and the innovation that comes from the suppliers. The high criticality of suppliers for the OEM’s success coupled with frequent supplier defaults observed in the industry warrants an investigation of supplier default risks which can inform industry practice and research.

Supplier portfolios from "Who Supplies Whom" database

The database "Who Supplies Whom" published by SupplierBusiness, a research company focusing on automotive supply base issues, is the starting point for our data collection. The data base contains comprehensive information about current car models, components, and modules as well as suppliers and covers around 80% of the volume in Europe and North America. Europe has been covered on this level of detail since 2002 and North America since January 2004. SupplierBusiness gathers the data through surveys of approximately 800 suppliers globally.

Based on this database, we constructed and analyzed supplier portfolios for three upper-class car models which have similar target customers and belong to a similar price range: the BMW 5-series (platform: E60; launch: 2003), the Audi A6 (platform: C6; launch: 2004), and the Mercedes E-class (platform: W211; launch: 2002).

Amadeus database for company ratings and default probability

Company ratings and default probabilities were obtained from the AMADEUS (Analyse MAjor Databases from EUropean Sources) data base provided by Bureau van Dijk-Electronic Publishing. AMADEUS focuses on European companies and provides standardized annual reports (for up to 10 years), and financial ratios as well as information on business activities and ownership structures on approximately 11 million companies throughout Europe. AMADEUS also offers a rating – the MORE (Multi Objective Rating Evaluation) rating, a credit risk product from ModeFinance[1]. The MORE rating is used for obtaining default probabilities. The MORE rating is based on the financial situation of the company and uses five categories of information as input (1: Solvency ratios; 2: Liquidity ratios; 3: Profitability ratios; 4: Interest coverage ratios; 5: Constraints on efficiency). The MORE rating methodology is very similar to Moody's methodology; an important difference between the two rating

[1] See www.modefinance.com for details.

systems is that Moody's takes both quantitative and qualitative information of a firm into account. The latter considers, for example, the financial policy, market share, competitive position and geographic/business diversification. In case that a uniform probability is assumed for all the suppliers in one portfolio, Moody's default probability is used.

Supplier switching cost estimation

As discussed earlier, exposure is difficult to measure in the automotive industry. Therefore, we have chosen switching costs as a proxy for exposure. While exposure measures the value subject to loss at default, switching costs measure the cost of switching away from a supplier after a default. Both concepts are part, component, module, system, and supplier market specific.

Estimating a dollar value of switching cost of a certain component is almost impossible for a broad range of components. Therefore, we aimed at assessing how difficult it is to switch away from a supplier of a certain component. Based on a standardized questionnaire, multiple experts were asked to estimate the switching cost for each component on a five-point rating scale (1: very low, 2: low, 3: medium, 3: high, 5: very high), which we denoted as switching cost rating (SCR).[2] Thus, it is important to note that these "switching costs" are measured on an arbitrary unit. It is not a monetary value as in the common credit risk distributions. And an assumption made is that the switching cost ratings of suppliers are linear; hence it is allowed to add the switching cost of suppliers together. This assumption is necessary to justify the use of switching cost ratings as exposures.

A key criterion for selecting the informants – who assess the supplier switching costs – is the knowledge and familiarity of the informants with the topic under investigation (Wagner, Rau, and Lindemann, 2010). Therefore, we selected two informants that were familiar with the supply markets and the components provided to automotive OEMs. We calculated interrater agreement on the rating of

[2] The complete questionnaire and the coded answers can be obtained from the corresponding author.

the 132 components in the questionnaire. 90% of the differences of the ratings were within one rating class. This shows that there is a relatively high level of interrater agreement.

The switching cost rating of the individual components received were transferred to a switching cost rating. Since the unit of analysis in the CreditRisk+ model is the individual supplier, not a component, it was necessary to aggregate the SCRs of the components to that of the supplier. For suppliers supplying multiple components there are three different possibilities to calculate the SCRs of suppliers from the SCRs of the components:

- SCR of supplier = Sum of SCRs of all components in the supply scope (*scenario I*)
- SCR of supplier = Mean of SCRs of all components in the supply scope (*scenario II*)
- SCR of supplier = Max of SCRs of all components in the supply scope (*scenario III*)

Scenario I assumes that the SCRs of components are linear and can be added together. On the one hand, this assumption seems to be reasonable, as the more components the supplier delivers, the higher the switching cost. But on the other hand, the assumption has a disadvantage. If one supplier delivers five very simple components, all with SCR of 1, the supplier has finally a SCR of 5, which is equal to a supplier which delivers a very difficult component with SCR of 5. This may not be the case in reality. Following scenario I the supplier can receive a SCR bigger than 5.

Scenario II takes the average value of SCRs of all the components in the supply scope as the rating of supplier. In this case, the disadvantage of adding up the ratings in scenario I is avoided. If a supplier supplies 5 components with SCR of 1, the supplier receives a SCR of 1. Following scenario II the supplier SCR ranges from 1 to 5.

Scenario III assumes that the most difficult component to replace in the supply scope is decisive for the SCR of a supplier. For instance, if one supplier delivers two components, one with SCR of 4 and the other with 3, the supplier receives a SCR of 4. Similar to scenario II, the supplier SCR is also between 1 and 5 under scenario III.

Depending on the method of aggregation, the SCRs of the suppliers have different values. In the results section, all three scenarios are examined in the CreditRisk+ model.

Supplier default correlation

Wagner, Bode, and Koziol (2009) find that in the German automotive industry default dependency among suppliers often exists and can have significant consequences. They identify several sources of default dependency between suppliers that can also be found in the German automotive industry. First, cooperative relationship between automotive suppliers, for example, exchanging explicit and tacit information, or engaging in joint venture projects can have the consequence that strategic decisions of suppliers are similar. Second, raw material price increases may have high impact on the profitability of all suppliers with the same factor input. Third, automotive suppliers face similar challenges because of the characteristics of the industry. Due to the highly concentrated market, there are only a few large and powerful automotive OEMs that can exert power over suppliers. Automotive suppliers are under constant pressure of cutting prices annually and providing innovations to OEMs. Fourth, the defaults of automotive suppliers are correlated because their financial health is all depending on the state of the economy and the automotive industry. In the current economic crisis there is drastic drop in the demand for cars, resulting in lower volumes at all automotive suppliers.

Results

Supply market and overlapping of supplier portfolios

In this section we analyze the supplier portfolios for the three car models BMW 5-series, Audi A6, and Mercedes E-class. Excerpts of the data are included in Appendix B.[3] Automotive suppliers usually supply to several automotive OEMs. Hence, the supplier portfolios for the three car models investigated

[3] The complete data sets pertaining to the three car models can be obtained from the corresponding author.

in this study also overlap (Figure 3). As such, we investigate the dynamics in triadic supply network relationships where a supplier works with two or three customers, and where the customers are direct competitors (Choi and Wu, InPress).[4]

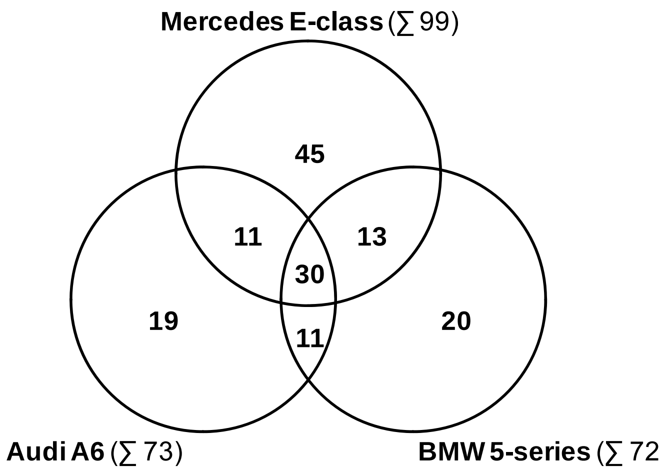


Figure 3. Overlap of the three car models' supplier portfolios

The supplier portfolio we were able to compile from our data sources contains 72 suppliers for the BMW 5-series, 73 for the Audi A6, and 99 for the Mercedes E-class. The total number of suppliers amounts to 149, of which 30 suppliers supply to all these three models. Mercedes E-class has 43 suppliers in common with the BMW 5-series and 41 suppliers with Audi A6. Therefore, the financial health of these common automotive suppliers is important to all three OEMs, and OEMs may have to cooperate in dealing with supplier defaults. For instance ZF delivers transmission system for all the three OEMs. If such a supplier goes bankrupt, it may receive support from its different customers. Hence choosing a supplier with broad customer base is better in terms of risk sharing once the supplier defaults.

[4] When supplier default correlation is considered – as we do in our model – the perspective on the supply network is extended even further to at least two customers and two suppliers. This reflects even better "the real and complex relationship that supply chain managers encounter every day."(Choi and Wu, InPress, p. 3).

Portfolio default distribution: The Bernoulli model

Portfolio of uniform DP and independent suppliers. As discussed in the Section "Modeling of defaults: The Bernoulli model" when the suppliers are independent and have a uniform default probability of p , the number of defaults in a portfolio L follows a Binomial distribution. Figure 4 shows the Binomial density distributions of three portfolios with different number of suppliers under the same uniform DPs. Table 3 shows the first moment E(L) and second moment V(L) of portfolio number of default L under different number of suppliers m and default probability p. $E[L]$and $V[L]$ are computed according to equation (7). One can see that the more suppliers the portfolio contains and the bigger the uniform DP, the higher the expected number and the variance of default events. This can also be observed from equation (7). Following this model if two portfolios have the same uniform default probability and independent suppliers, the bigger portfolio has higher risk regarding number of defaults.

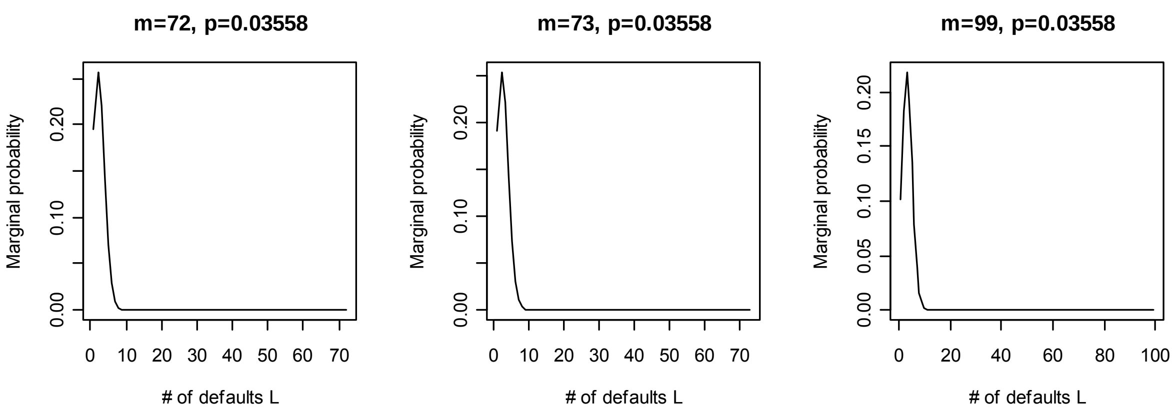


Figure 4. Binomial density distributions of loss statistics L under uniform DP 3.558%

Table 3. Default events modeling using Bernoulli model under assumptions of uniform DP and independence between suppliers

Moody's Letter rating		m=72		m=73		m=99	
	DP=p	E (L)	V (L)	E (L)	V (L)	E (L)	V (L)
Aaa	0.012%	0.009	0.009	0.009	0.009	0.012	0.012
Aa	0.038%	0.027	0.027	0.027	0.027	0.037	0.037
A	0.117%	0.085	0.084	0.086	0.086	0.116	0.116
Baa	0.366%	0.264	0.263	0.267	0.266	0.362	0.361
Ba	1.141%	0.822	0.812	0.833	0.824	1.130	1.117
B	3.558%	2.562	2.471	2.598	2.505	3.523	3.397
Caa-C	11.095%	7.988	7.102	8.099	7.201	10.984	9.765

Portfolio of different DPs and independent suppliers. Under the assumption of independent suppliers the distribution of $\mathbf{L}$ depends on the number of suppliers and the default probability of each supplier. The more suppliers the portfolio contains and the higher the default probability of each supplier is, the higher are the expected number of defaults $\mathbf{E}[\mathbf{L}]$ and variance $\mathbf{V}[\mathbf{L}]$**.** Applying equation (5), $\mathbf{E}[\mathbf{L}]$ and $\mathbf{V}[\mathbf{L}]$ are calculated for the three automotive supplier portfolios. Excerpts of the three datasets are included in Appendix B. Table 4 shows that the $\mathbf{E}[\mathbf{L}]$ and $\mathbf{V}[\mathbf{L}]$ of the Mercedes E-class are higher than the other two portfolios.

Table 4. Default events modeling with Bernoulli model with empirical DPs and independent suppliers

Supplier portfolios	Number of suppliers	E (L)	V (L)
BMW 5-series	72	2.17	1.72
Audi A6	73	3.25	2.25
Mercedes E-class	99	4.73	3.39

Bernoulli mixture model. Using a Bernoulli mixture model, the distribution of defaults can include the effect of the correlation between the supplier defaults. According to equation (11), the joint distribution function of the loss statistics depends on the distribution of the default probability **F**, which is assumed to be a multivariate normal distribution in the KMV model. Equation (6) can be rewritten as

$$\begin{aligned} P[L_1 = l_1, \dots, L_m = l_m] &= \int_{[0;1]^m} \prod_{i=1}^{m} {p_i}^{l_i}(1-p_i)^{1-l_i}\, d\boldsymbol{F}(p_{1,\dots,}p_m) \\ &= E\left[\prod_{i=1}^{m} {p_i}^{l_i}(1-p_i)^{1-l_i}\right] \cong Mean[\left[\prod_{i=1}^{m} {p_i}^{l_i}(1-p_i)^{1-l_i}\right] \end{aligned} \tag{15}$$

Equation (15) shows that it is possible to simulate the value of $\mathrm{P}[\mathrm{L}_1 = \mathrm{l}_1, \dots, \mathrm{L}_\mathrm{m} = \mathrm{l}_\mathrm{m}]$ using a random number generator for the multivariate normal distribution. The function “rmvnorm” of software R (R Development Core Team, 2008) offers such a solution.

Computation using CreditRisk+ model

In the Bernoulli model, the exposure is not included in the analysis – in the CreditRisk+ model it is. The model computes the portfolio loss distribution, the expected loss of each supplier, and the risk contribution at the given percentile level. The input information is the suppliers names, their exposure, mean default probabilities and the default rate volatility, and the sector split.[5]

Portfolio loss distributions. This section contains the portfolio loss distribution of the three supplier portfolios which are generated by the CreditRisk+ model. Because there are three scenarios of supplier switching cost ratings, which is discussed in the section ”Supplier switching cost estimation”, there are accordingly three different scenarios of exposures. So finally there are nine different cases (3

[5] The data can be obtained from the corresponding author.

portfolios times 3 exposure scenarios). Table 5 summarizes the risk percentiles of these cases. The loss distributions of the three car supplier portfolios are compared under each scenario.

Summary of risk percentiles. The risk percentiles are derived from the portfolio loss distributions. By comparing the default level of risk percentiles, a buying firm can determine the risk of the portfolios.

Under the same scenario, for instance scenario I, the 99 percentile loss level of the BMW 5-series portfolio is 69, the Audi A6 is 94, and the Mercedes E-class is 96. That is, the Mercedes E-class portfolio has also the highest expected loss value, which is denoted as mean value in the table.

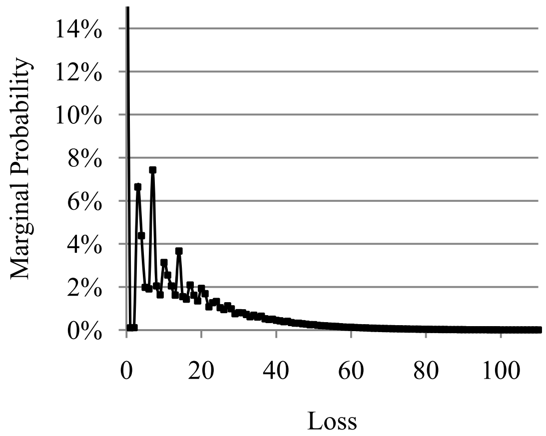
Across the three scenarios, the default loss under scenario I is significantly higher than under scenario II and III. The difference between scenario II and III is rather small. This is because in scenario I the SCRs of suppliers, which are used as exposures in the modeling, are systematically higher than that of scenario I and II.

Table 5. Risk Percentiles of the three portfolios under three different scenarios

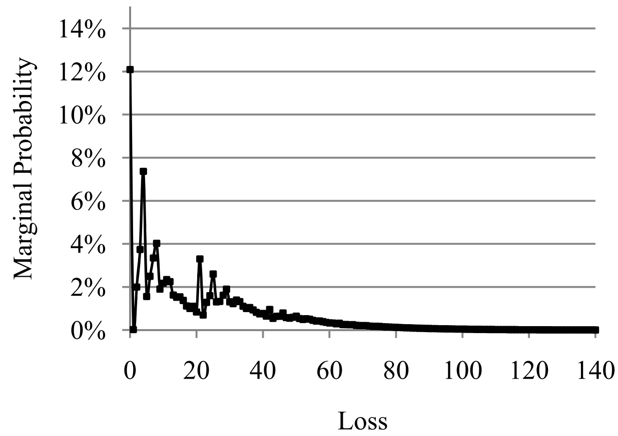
Percentile	Loss amount								
	BMW 5-series Scenario I	BMW 5-series Scenario II	BMW 5-series Scenario III	Audi A6 Scenario I	Audi A6 Scenario II	Audi A6 Scenario III	Mercedes E-class Scenario I	Mercedes E-class Scenario II	Mercedes E-class Scenario III
Mean	13	7	7	22	10	11	25	15	16
50	7	4	4	15	8	9	19	12	13
75	19	10	11	32	14	16	35	21	22
95	45	22	23	65	26	29	67	37	39
97.5	56	27	28	77	31	34	80	44	46
99	69	33	35	94	37	40	96	52	55
99.5	80	38	40	106	41	45	108	59	61
99.75	90	42	45	118	46	50	120	65	68
99.9	104	48	51	133	51	56	135	72	76

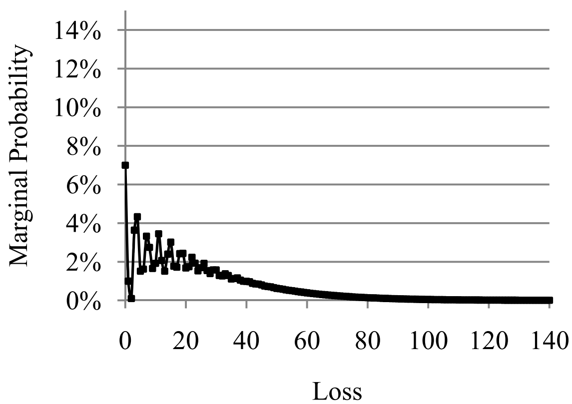
Portfolio loss distributions. In the following Figures, the loss distributions for the supplier portfolios of the three investigated car models are depicted. We applied the Creditrisk+ framework to the three scenarios. Figure 5 summarizes the portfolio loss distributions under scenario I (i.e., sum of SCRs of all components in the supply scope).

BMW 5-series portfolio loss distribution

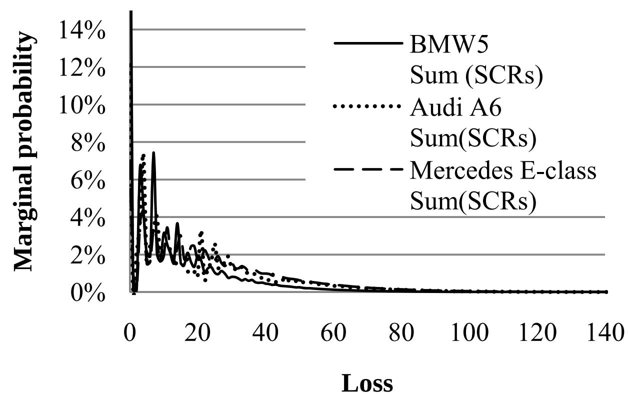


Audi A6 portfolio loss distribution





Mercedes E-class portfolio loss distribution



Comparison of loss distributions

Figure 5. Portfolio loss distributions under scenario I

Figure 6 summarizes the portfolio loss distributions under scenario II.

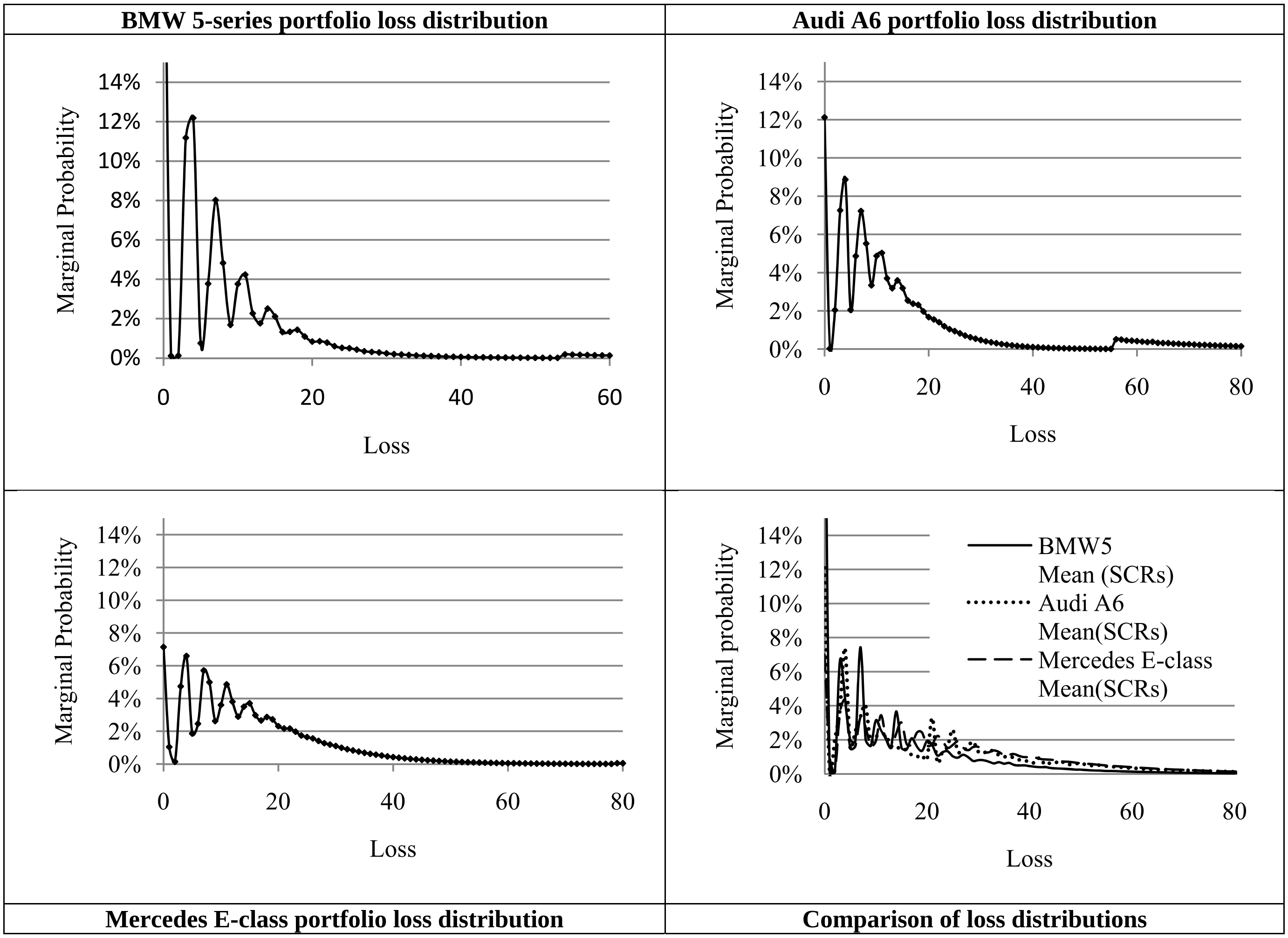
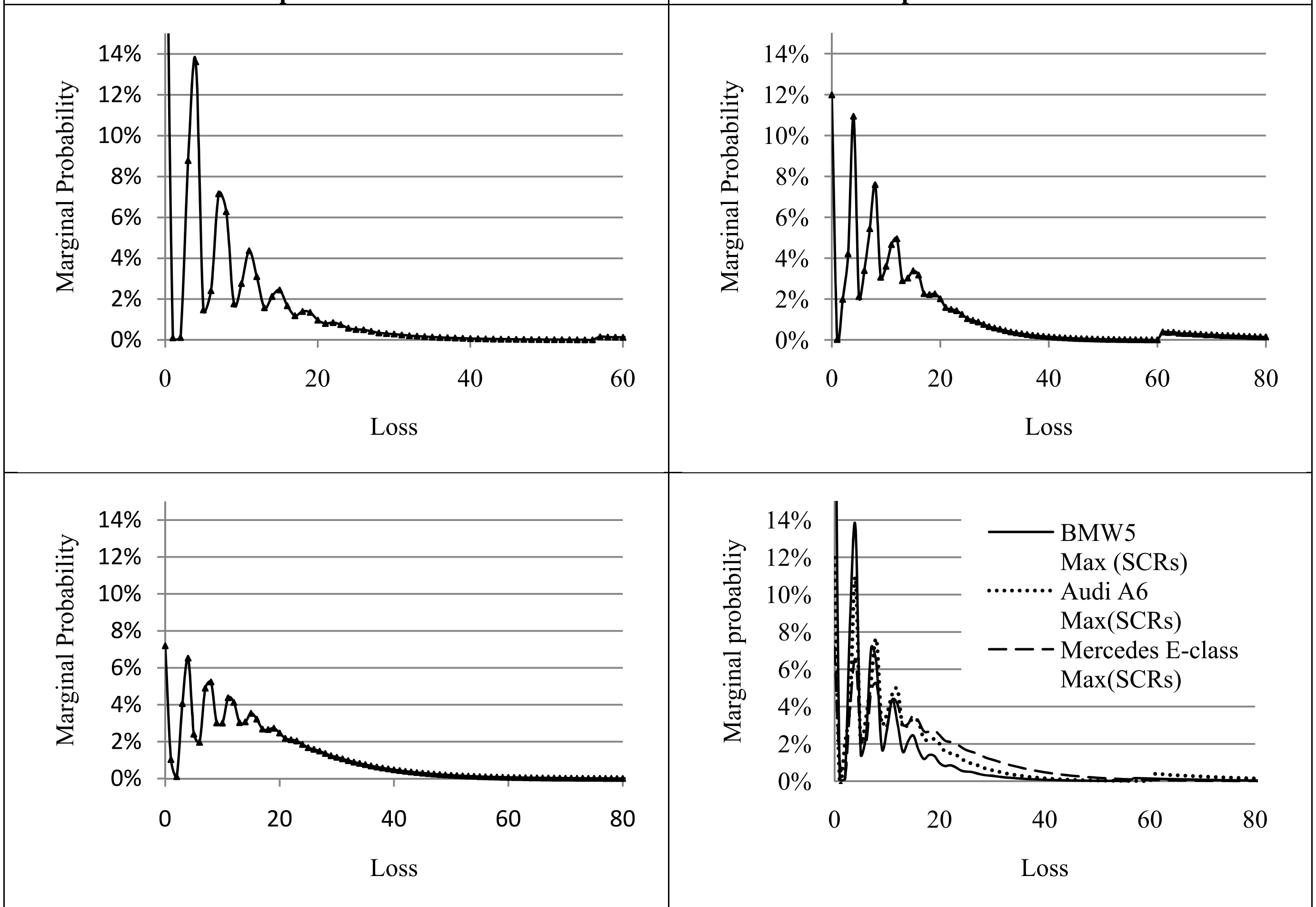


Figure 6. Portfolio loss distributions under scenario II

Figure 7 summarizes the portfolio loss distributions under scenario III.

BMW 5-series portfolio loss distribution	Audi A6 portfolio loss distribution



Mercedes E-class portfolio loss distribution	Comparison of loss distributions

Figure 7. Portfolio loss distributions under scenario III

Recall that the scenarios were constructed to capture the OEMs' exposure to supplier default risk. The absolute values on the x-axis are only limited meaningful. Figure 5, for example, shows that, in the Audi A6-portfolio, the probability of incurring a loss of 20 (e.g., defaulting of 4 suppliers with a SCR rating of 5) during the next year is about 2%.

Risk contributions and pairwise correlations. To measure risk contribution – the contribution of the supplier to the unexpected loss of the supplier portfolio – we set the percentile level to 99th percentile. The sum of the risk contributions of all the suppliers in the portfolio should be equal to the loss of 99th percentile. Table 6 summarizes the sum of risk contributions and the 99th risk percentile. They are slightly different. This could be due to the accuracy limit of the model used.

μ_A and μ_B denote the expected number of defaults of supplier A and B in a certain time period, and σ_A and σ_B denote the standard deviation of default probabilities of supplier A and B. For instance, in the supplier portfolio of the BMW 5-series, $\mu_1 = \sum_A p_A = 2.17$, $\sigma_1 = \sum_A \sigma_A = 1.79$. The default probability of supplier ZF is 0.4% and that of supplier Webasto is 1.2% (see Appendix B). The default correlation between these two suppliers is $(0.4\% * 1.2\%)^{1/2} \times (1.79/2.17)^2 = 0.47\%$.

Table 6. Sum of risk contributions at 99th risk percentile

	BMW 5-series			**Audi A6**			**Mercedes E-class**		
	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III
99th risk percentile	69	35	35	94	37	40	96	52	55
Sum of risk contributions	65	25	27	87	28	32	86	45	48

Implications and Conclusion

In this paper, credit risk models are introduced to the supply chain context to quantify supplier default risk. The Bernoulli model and the CreditRisk+ model are examined for their applicability. The models are applied to three automotive supplier portfolios: BMW 5-series, Audi A6, and Mercedes E-class. The portfolio default distributions and the portfolio loss distribution are derived for the three supplier portfolios. The results provide various information which support the automotive OEMs in supply chain risk quantifications and management from various aspects.

First of all, the credit risk models provide the buying firm a new perspective and an integral framework for analyzing the different risk aspects of the supplier portfolio, mainly the default probabilities and exposure of suppliers and the default correlation structure among suppliers. Hence the first important message from the models is that knowing the suppliers is important. OEMs should pay attention to the risk attributes of the suppliers, for instance the financial health of the supplier, the availability of alternative suppliers and so on. The data collection process itself enables the OEM to know its own supplier portfolio better in a systematic way. Based on the collected data, the OEM may keep a watch list of suppliers which have high default probability in the next year. The OEM may also analyze the suppliers with very high exposure and identify them as strategic partner or consider the development of alternative suppliers.

Second, the outputs of the models may support various decision making processes in supply chain risk management. With the default event distribution and the loss distribution of the supplier portfolio, the OEMs can plan its human and capital resources more efficiently. For instance, if the analysis shows that the default risk of the portfolio is high in the next year, it is perhaps advocated to invest more resources in managing the supplier base, enhancing supplier development or switching away from a supplier with high default probability. The portfolio loss distribution supports buying firms in creating risk mitigation strategies, for example buying insurance. The risk contribution of each supplier from the CreditRisk+ model advocates risk-benefit balance thinking in supplier evaluation processes and assists the portfolio management, for instance reducing the portfolio extreme loss by removing suppliers with high risk contributions.

However it is also important to be aware of the limitations of our approach. Before implementing the models, the OEMs need to identify and understand the inaccuracy in the input dataset and the assumptions made in the models itself and finally consider these aspects for the interpretation of the model output.

To sum it up, credit risk models can be adapted to assess supplier default risk. As the application of credit risk models requires a large amount of information on the suppliers, the buying firms (including OEMs) are in the best position to do the analysis. The analysis process may become a tool for OEMs to quantify and manage supplier default risk. The models can also be applied to other industries where the buying firm is concerned about risk of supplier defaults.

Several areas of further research can be highlighted. First, the study can be extended to examine the applicability of other industrial credit risk models, for instance the KMV model. Second, in this paper, only the first-tier suppliers were considered. It would be interesting to examine the applicability of the credit risk models to multi-stage supply chains, taking into consideration various design and structural characteristics (e.g., a multiple sourcing vs. a single sourcing strategy) and the second-tier suppliers and suppliers further upstream in the supply chain into account. Third, researchers may try to apply credit risk models to model a broader spectrum of supply chain risk, for instance delivery delays.

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Appendix

Appendix A. List of notations and abbreviations

Notation	Meaning
L	It denotes the total number of defaults in a portfolio in the Bernoulli model.
L_i	The Bernoulli variable denoting default of counterparty i.
$\boldsymbol{L}$	A Bernoulli loss statistics. It is a vector of random variables $\boldsymbol{L} = (L_1, \dots L_m)$
$\tilde{L}$	The loss of an individual obligor
i	Index of a counterparty (a supplier or an obligor), $i = 1, \dots, m$
m	The number of counterparties (suppliers or obligors)
p	A assumed uniform default probability for a portfolio
p_i	The observed default probability of counterparty i. In Bernoulli mixture model it means one realization of random number P_i.
D	The event that the obligor defaults in a certain period of time (most often one year).
$P(D)$	the probability of D
1_D	A Bernoulli variable
$E[L]$	The expected value of default distribution L
$V[L]$	The variance of default distribution L
P_i	The randomized default probability of counterparty i
$\boldsymbol{P}$	The vector of the randomized default probabilities of all the counterparties $\boldsymbol{P} = (P_1, \dots, P_m)$
P	The uniform random default probability in the Bernoulli mixture model
$\overline{p}$	The mean value of the uniform random default probability P in the Bernoulli mixture model.
$\boldsymbol{p}$	The vector of the mean default probabilities $\boldsymbol{p} = (p_1, \dots, p_m)$. In Bernoulli mixture model it means one realization of $\boldsymbol{P}$.
λ_i	The observed default intensity of counterparty i. In Poisson mixture model it means a realization of random number Λ_i.
$\boldsymbol{\lambda}$	The vector of realization of random default intensities $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_m)$.
L'	The portfolio number of default from Poisson model both in case of independent counterparties and in the Poisson mixture model.
Λ_i	The randomized default intensity
$\boldsymbol{\Lambda}$	The vector of randomized default intensities, $\boldsymbol{\Lambda} = (\Lambda_1, \dots, \Lambda_m)$.
$\boldsymbol{F}$	A multivariate distribution. In Bernoulli model it represents the distribution of $\boldsymbol{P}$ with support in $[0, 1]^m$. In Poisson model it represents the distribution of $\boldsymbol{\Lambda}$ with support in $[0, \infty)^m$.
A, B	Denote two suppliers in CreditRisk+ model
ρ_{AB}	Default correlation of two suppliers A and B
μ_A, μ_B	The expected number of default in a certain time period.
k	Index of sectors in CreditRisk+ model
n	The number of sectors
θ_{Ak}, θ_{Bk}	Sector decomposition of supplier A and B
μ_k	The long-term annual average number of defaults of sector k
σ_k	Standard deviation of number of defaults of sector k
σ_1	Standard deviation of number of defaults of the single sector if all the suppliers are allocated to the same sector
μ_1	The long-term annual average number of defaults of the single sector 1.
p_A	Default probability of supplier A
σ_A	The standard deviation of default probability of supplier A

Appendix B. Excerpts of supplier portfolio data

BMW 5-series Supplier name	Exposure Scenario I	Exposure Scenario II	Exposure Scenario III	Mean Default Rate	Default Rate Standard Deviation	Sector split Automotive Industry
A. Raymond	10	3.3	4.5	0.25%	0.29%	100%
AGC Automotive	3	3.0	3.0	43.00%	11.86%	100%
Alcoa	9.5	4.8	5.0	0.01%	0.05%	100%
Allevard Rejna	4.5	4.5	4.5	0.40%	0.74%	100%
Alpine	5	2.5	2.5	3.70%	4.71%	100%
Alu-Guss	1	1.0	1.0	0.25%	0.29%	100%
Arques	2.5	2.5	2.5	1.20%	1.87%	100%
ArvinMeritor	7.5	3.8	4.0	3.70%	4.71%	100%
Behr	3.5	3.5	3.5	1.20%	1.87%	100%
Benteler	9	4.5	5.0	1.20%	1.87%	100%
Beru	6.5	3.3	3.5	0.20%	0.29%	100%
BorgWarner	3.5	3.5	3.5	1.20%	1.87%	100%
Bosch	19.5	3.9	5.0	0.40%	0.74%	100%
Boysen	3.5	3.5	3.5	1.12%	1.87%	100%
...	...	...	...	...	...	...
Visteon	4	4.0	4.0	3.70%	4.71%	100%
WABCO	4.5	4.5	4.5	2.00%	1.87%	100%
Webasto	4	4.0	4.0	1.20%	1.87%	100%
ZF	32	4.0	5.0	0.40%	0.74%	100%
Mean	7.0	3.3	3.6	0.03	0.02	1
Max	36.0	5.0	5.0	0.45	0.12	1
Min	1.0	1.0	1.0	0.00	0.00	1
Median	5.0	3.3	3.5	0.01	0.02	1
Standard Deviation	6.2	0.8	0.9	0.07	0.03	0
Sum	502.5	234.3	256	2.17	1.79	72

Audi A6 Supplier name	Exposure Scenario I	Exposure Scenario II	Exposure Scenario III	Mean Default Rate	Default Rate Standard Deviation	Sector split Automotive Industry
AGC Automotive	3	3.0	3	43.00%	11.86%	100%
ArvinMeritor	8	4.0	4.5	3.70%	4.71%	100%
Autoliv	3	3.0	3	0.35%	0.74%	100%
Avon	4	4.0	4	48.00%	11.86%	100%
Benteler	19	3.8	4.5	1.20%	1.87%	100%
BorgWarner	8	4.0	4.5	1.20%	1.87%	100%
Bosch	11	3.7	4.5	0.40%	0.74%	100%
Brembo	2.5	2.5	2.5	0.35%	0.74%	100%
Brose	6.5	3.3	3.5	0.07%	0.12%	100%
Calearo	2	2.0	2	0.35%	0.74%	100%
Catem	4	4.0	4	1.33%	1.87%	100%
CML Innovative Technologies	3	3.0	3	0.40%	0.74%	100%
Continental	31.5	3.2	4.5	1.20%	1.87%	100%
Denso	3.5	3.5	3.5	5.70%	4.71%	100%
...	...	...	...	...	...	...
Voestalpine	5	5.0	5	1.20%	1.87%	100%
Volkswagen Braunschweig	7.5	3.8	5	1.20%	1.87%	100%
Webasto	4	4.0	4	1.20%	1.87%	100%
ZF	22.5	4.5	5	0.40%	0.74%	100%
Mean	6.4	3.2	3.5	0.04	0.03	1
Max	31.5	5.0	5.0	0.48	0.12	1
Min	1.0	1.0	1.0	0.00	0.00	1
Median	4.0	3.2	3.5	0.01	0.02	1
Standard Deviation	5.9	0.8	0.9	0.11	0.03	0
Sum	468.5	235.1	256.0	3.25	1.91	73

Mercedes E-class Supplier Name	Exposure Scenario I	Exposure Scenario II	Exposure Scenario III	Mean Default Rate	Default Rate Standard Deviation	Sector split Automotive Industry
A. Raymond	6.5	3.3	3.5	0.25%	0.29%	100%
AGC Automotive	3	3.0	3	43.00%	11.86%	100%
ArvinMeritor	3.5	3.5	3.5	3.70%	4.71%	100%
Autoliv	7	3.5	4	0.35%	0.74%	100%
BASF	1	1.0	1	0.40%	0.74%	100%
Behr	7	3.5	3.5	1.20%	1.87%	100%
Beru	13.5	3.4	4	0.20%	0.29%	100%
Bleistahl	4	4.0	4	3.70%	4.71%	100%
Borgers	8.5	2.8	3.5	1.20%	1.87%	100%
BorgWarner	3.5	3.5	3.5	1.20%	1.87%	100%
Bosch	36	3.3	5	0.40%	0.74%	100%
Brembo	2.5	2.5	2.5	0.35%	0.74%	100%
Brose	9	3.0	3.5	0.07%	0.12%	100%
Continental	39	3.0	5	1.20%	1.87%	100%
...	...	...	...	...	...	...
Wagon	4	4.0	4	7.10%	4.71%	100%
Webasto	8	4.0	4	1.20%	1.87%	100%
Witzenmann	4.5	2.3	3.5	0.40%	0.74%	100%
ZF	20.5	4.1	5	0.40%	0.74%	100%
Mean	6.7	3.2	3.5	0.05	0.03	1
Max	39.0	5.0	5.0	0.48	0.12	1
Min	1.0	1.0	1.0	0.00	0.00	1
Median	4.0	3.3	3.5	0.01	0.02	1
Standard Deviation	6.6	0.9	1.0	0.11	0.04	0
Sum	667.0	319.8	346.5	4.73	2.92	99