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# Data-driven risk measurement of firm-to-firm relationships in a supply chain



Byung Kwon Lee<sup>a</sup>, Rong Zhou<sup>a,\*</sup>, Robert de Souza<sup>a</sup>, Jaehun Park<sup>b</sup>

<sup>a</sup> The Logistics Institute - Asia Pacific, National University of Singapore, 21 Heng Mui Keng Terrace, Singapore 119613, Singapore

<sup>b</sup> Technology Analysis Team, Defense Agency for Technology and Quality, Jinju 660-031, Republic of Korea

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## ABSTRACT

Business entities are always exposed to potential risks as they are interconnected in a supply chain. The performance of a business entity would be disturbed by the realization of risks, and substantial effort would be required to bring its performance back to the previous level. This study proposes an approach to measure the degree of risk caused by a supplier to the manufacturer by considering the interaction between them in a supply chain. A supply chain simulation is developed based on a real business case for an assemble-to-order industry, and the operational dataset is used to measure the degree of risk. A binary response model with a latent variable is employed to estimate the degree of risk under different conditions. Sensitivity analyses are conducted using a numerical experiment. The results show that decremental demand outperforms incremental demand when the lead time of supply is the performance measure. In terms of the degree of risk, the converse is found to be true when the fulfillment rate is the performance measure. The proposed approach could be used to quantify the risk level, identify the bottleneck supplier, and provide a guide for updating the operational settings.

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## 1. Introduction

It is important for a firm to understand its risk exposure level within the supply chain, especially the risk caused by its suppliers. This understanding can help it to choose (1) appropriate suppliers in pre-disruption and/or (2) alternative suppliers in post-disruption, without increasing the network's risk exposure level. As a supply chain member may have limited information about the business environment and activities of other members, it is imperative to postulate a framework for determining the risk exposure level for the supply chain as a whole, as well as for each member.

Much research has been conducted to identify firm risk. Chopra and Sodhi (2004) categorized supply chain risks (disruptions, delay, systems, forecast, intellectual property, procurement, receivables, inventory, and capacity) and the drivers of each risk with examples. Additionally, they proposed mitigation approaches and their trade-off relationships. Sheffi and Rice (2005) introduced a disruption profile that describes the various stages of disruption and proposed two ways (redundancy and flexibility) to increase a firm's resilience, in order to counteract threats and the occurrence

of supply chain disruptions. Moreover, Zsidisin and Wagner (2010) examined the relationships between supply chain risk perception and disruption occurrence, as well as between resilience practices and the effect of supply disruptions, through a factor analysis of the empirical data collected from various industries. Their findings indicate that the higher the perception of a risk source, the less frequently the firm will experience the effects of supply disruptions. According to Tazelaar and Snijders (2013), the net effects of specialized and general expertise on assessment performance are negligible. They recommended that risk assessment could benefit from less reliance on intuitive judgment, an increase in feedback on the accuracy of previous assessments, and the involvement of model-based prediction in the assessment process. In addition to identifying the risk associated with decision makers, Neiger et al. (2009) proposed a risk identification methodology, based on value-focused process engineering, by treating a supply chain as a set of interconnected value-adding processes and risk reduction as a business objective, as well as including risk sources.

Hemrit and Arab (2012) conducted an extensive literature review and discussed the causes of operational risk and benefits of managing such risk for financial firms. Regarding risk assessment from the financial perspective, value-at-risk has become the most popular measure for quantitatively representing the degree of risk (Göb, 2011). This measure can estimate the amount of recovery effort required for risk events for a given amount of loss as well as the recovery duration (Zhang et al., 2012). In addition, Fihini et al.

\* Corresponding author.

E-mail addresses: [iselbk@nus.edu.sg](mailto:iselbk@nus.edu.sg) (B.K. Lee), [tlizr@nus.edu.sg](mailto:tlizr@nus.edu.sg) (R. Zhou), [rdesouza@nus.edu.sg](mailto:rdesouza@nus.edu.sg) (R. de Souza), [pjh3479@dtq.re.kr](mailto:pjh3479@dtq.re.kr) (J. Park).

(2010) integrated operational and financial risk scores into a single risk measure, expressing the former as the event frequency with an ordinary scale of severity, and the latter as the probability of losses resulting from defaults in payment. A logistics regression model was used to estimate the financial risk score, and the integration score was estimated by linearly combining the two risk scores, taking into account their variances. Figini and Giudici (2013) targeted a non-financial firm with data available only on an ordinal scale, constructed a loss contingency table showing the frequency of risk for a business line and event type, and proposed a stochastic dominance index measure to estimate the operational risk associated with a business line and event type combination. The proposed stochastic dominance index was bounded between 0 (when the risk event never appears) and 1 (when the risk event has the highest severity).

Some studies have considered identifying the expected risk associated with the relationship among supply chain members. Mizgier et al. (2012) studied the dynamics of the behaviors of the supply chain network in an uncertain environment using the agent-based modeling approach. The objective was to observe the propagation effect of a firm's local default on the global performance of the supply chain network; financial default occurs when a firm's working capital hits the threshold level (which is a fraction of the average working capital of all the firms), and the performance measure is the percentage of the working capital utilized in the production of the whole system at a certain time. Moreover, Mizgier et al. (2013) proposed an approach for a focal firm to identify high-risk suppliers (potential bottlenecks) by estimating the loss distribution due to hazard events via Monte Carlo simulation in supply chain networks. The proposed loss distribution approach estimates the propagation of hazard events. This approach is superior compared to the other social network approaches investigated by Kim et al. (2011) because it considers the features of the network structure to identify the potential risky suppliers. Additionally, Kim et al. (2011) proposed the structural characteristics of supply chain networks using social network analysis. The authors described the modeling metrics of social network analysis, constructed a conceptual framework for analyzing a supply chain network, and demonstrated it in two network types, namely, material flows and contractual relationships. Through empirical investigation, they proposed practical implications related to the application of social network analysis for supply chain networks. Samvedi et al. (2013) quantified supply chain risks and proposed a risk index between 0 and 1 by integrating a fuzzy analytical hierarchy process as well as the fuzzy Technique for Order of Preference by Similarity to Ideal Solution. They conducted an extensive survey of 150 companies and used the participants' responses as the input data (expert judgments) for the proposed methodology.

Braunscheidel and Suresh (2009) defined the supply chain agility of a firm as the capacity to adapt or respond to market changes as well as potential and actual disruptions. Using the

partial least squares technique, they examined the extent of agility for organizational practices such as internal integration, external integration with key suppliers and customers, and external flexibility. Wagner and Bode (2008) conducted a cross-sectional survey and collected 760 responses from top-level executives in Germany. They empirically examined the association between risk sources and risk effect on supply chain performance. According to their analysis, both demand and supply side risks have significantly negative associations with supply chain performance. However, risk management is positively associated with performance at a significant level. In addition, Manuj et al. (2014) assessed the effectiveness of the four supply chain risk approaches (hedging, assuming, postponement, and speculation) on the different conditions (high and low) of supply and demand risks. They found that the hedging and assuming strategies perform better in contexts involving high supply and demand risks, respectively. Further, da Cruz and Lind (2012a, 2012b, 2013) analyzed the network of trading in financial markets via the dynamic behaviors of agents over time, by taking into account the incoming (consumption) and outgoing (production) connections of each agent, and estimated the degree of economic quantity (labor, wage, price, etc.). The authors considered a collection of agents operating as energy transducers into the economic space, and described the interaction between agents as internal energy.

This study measures the expected degree of risk in the relationship between the two supply chain members (supplier and manufacturer) and expresses the bounded results [0,1], to provide a comprehensive and data-driven understanding of the expected risk exposure in a firm-to-firm relationship. Unlike Fihini et al. (2010) and Figini and Giudici (2013), this study derives the degree of risk in a firm-to-firm relationship. That is, the frequency and severity of risk events are expected to be observed in the interaction activities of the two firms. In addition, although most of the prior studies (e.g., Manuj et al., 2014; Mizgier et al., 2013; Samvedi et al., 2013; Wagner and Bode, 2008) attempted to find the causes of risk related to the deliverables and/or production process at the supplier's side, as well as the effects on performance disruption at the manufacturer's side (Fig. 1), this study examines the effects of supplier-side decision activities on the manufacturer-side performance disruption (Fig. 2). In this particular approach, the risk sources delivered to the manufacturer are supposed to have originated at the stage of input decision activities; eventually, the sources would influence the performance disruption of the manufacturer. Compared to the three studies (da Cruz and Lind, 2012a, 2012b, 2013) that paid attention to the dynamic interactions between agents over time, this study characterizes the historical interactions and analyzes the effect of the input decisions of suppliers on the output deliverables (performance) of a manufacturer, considering the flows along the three stages, namely, the input decision activities, internal process, and output deliverables.

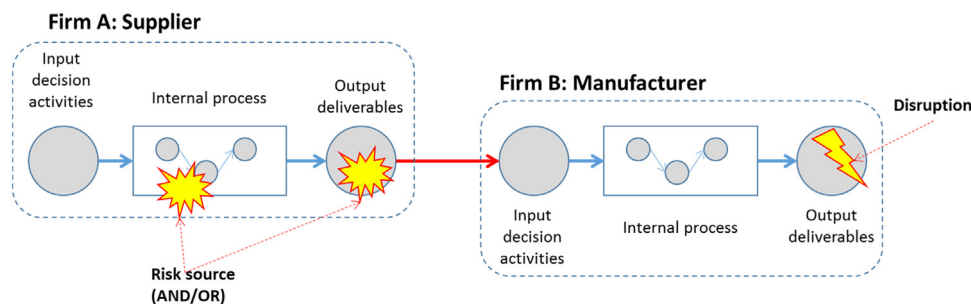


Fig. 1. Risk analysis view: deliverables of a supplier would lead to the performance disruption of a manufacturer.

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