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1. Risk perception and decision making in the supply chain: theory and practice

1.1 Introduction

All courses of action are risky, so prudence is not avoiding danger (it’s impossible), but calculating risk and acting decisively. Make mistakes of ambition and not mistakes of sloth. Develop the strength to do bold things, not the strength to suffer. Niccolò Machiavelli (1469–1527), The Prince (1532)

For over 60 years, academics and practitioners from different backgrounds, including psychology, sociology and management, have studied the perception of risk and how different decision making affects daily life and business activities. Although it is almost 600 years since Machiavelli stressed the importance of calculation of risk and effective response to it, approaches to risk measurement and assessment, and to decision making in risky situations, continue to develop and evolve. In the business world, managers strive to find ways to understand how different internal and external factors influence risk, how to judge and interpret the available evidence on the possibility of loss, and how to take individual actions to manage the risk (Slovic, 2000). In this decade, a number of risk management frameworks (e.g. ISO 31000) have been proposed and employed in different areas. These frameworks provide foundations and building blocks for managers to collect available data to analyse risk. Most importantly, such frameworks allow managers to gather knowledge intellectually, to properly judge their experience and to assess the current situation, so as to enter into the most appropriate decision.

Against a background of massive change in many different fields, innovations such as new supply chain structure (e.g. Global Supply Chain, Belt and Road opportunities, Wang, 2016), policy change (e.g. Paris Agreement, Jacobs, 2016, new tariffs in trade war) and the development of new technology (e.g. Internet of things (IoT), Ben-Daya et al., 2017; AI, Gunasekaran and Ngai, 2014; block chain, Rahmadika and Rhee, 2018) are increasing the number and complexity of risk-bearing activities in the upstream supply network. These supply chain risks are diverse, and include, for example, supply interruption, product recall/withdrawal, terrorism and environmental and ethical issues. They are both complicated and very difficult to deal with, since they involve different entities in the supply chain (Tse et al., 2018). As such, they present particular challenges in supply chain risk management (SCRM), and cannot be evaluated using a solely qualitative or quantitative approach. Moreover, it is important to bear in mind that the response actions should not strengthen the tolerances or the risk impact on the supply chain, but should focus on building a more resilient supply chain to improve the company competitiveness.

Driven by the awareness of and serious concerns regarding risk and decision making in supply chain research, this special issue aims to highlight the contemporary research that is using various methodologies, including mathematics modelling, survey-based research, case study-based research, panel data research, data analytics, integrated decision-making model and review studies. It includes a total of 12 research studies, which can be categorised into the following dimensions.

The authors wish to thank the contributors of this special issue, and the editor of Industrial Management & Data Systems – Professor Hing Kai Chan for encouragement and support. In addition, the authors would like to thank the anonymous reviewers who provided excellent review comments and helped the authors’ contributors improve their research works.
2. Empirical research of SCRM practices and strategies

2.1 Risk management and firm performance: the moderating role of supplier integration
Shou et al. (2018) conduct a survey-based research to investigate the performance effect of SCRM. The performance is studied in three aspects, namely, financial performance, operational efficiency and flexibility. An SCRM model is developed and examined by employing structural equation modelling techniques with 652 global samples. Shou et al. apply information processing theory to crystallise the performance impact of SCRM. The results indicate that SCRM positively influences flexibility and operational efficiency, and impacts indirectly on financial performance. Moreover, the supplier integration practice increases the impact of SCRM on operational flexibility, but does not moderate the relationship between SCRM and operational efficiency.

2.2 Managing hazards of the make-buy decision in the face of radical technological change
Park (2018) conducts a secondary data study to investigate the make-buy decision when a firm is facing radical technological change, which could represent either an opportunity or a risk to the company. The sourcing decision becomes critical, and may lead to exchange and hierarchical hazards. By evaluating 12 years’ panel data, the study finds that the in-house retention of outsourced component knowledge and exploratory technological experience are important in this context, and are significant moderating factors which facilitate the improvement of the make and buy strategy.

2.3 The role of consistency between objective and perceived environmental uncertainty in SCRM: a case study
Yu et al. (2018) investigate how consistency between objective and perceived uncertainty in the environment affects the supply chain flexibility to cope with supply chain risk. They adopt the case study approach to distinguish different effects of objective and perceived environmental uncertainty on supply chain flexibility. Four in-depth Chinese case studies (two environmental instrument companies and two power generation companies) are conducted in order to understand how different types of SCRM strategies, namely, logistics flexibility and relationship flexibility, cope with complex and turbulent environments.

3. Risk management and decision support system model in supply chains

3.1 Decision modelling of risks in pharmaceutical supply chains (PSCs)
Moktadir et al. (2018) develop a decision-making model to identify risks associated with PSCs. An integrated AHP and Delphi decision-making approach is proposed and validated by a pharmaceutical case study, and finds that supply-related risks such as fluctuation in imports arrival, limited information sharing, failure of key supplier and non-availability of materials should be prioritised over other more generic risks in the supply chain, including operational, financial and demand-related risks. In order to develop resilience capabilities of PSCs, managers should consider the importance of different types of supply chain risks.

3.2 Managing supply chain risks and delays in construction projects
Panova and Hilletofth (2018) develop a simulation model to investigate how construction delay is influenced by supply chain disruption risk. Their study also includes a qualitative and quantitative method for risk assessment. The findings indicate that construction delays are influenced by the two traditional risk dimensions, i.e., the magnitude and the probability of disruption, but also that the researcher should not overlook the time factor. Based on an empirical analysis, the study proposes increasing the safety stock of construction materials at the distribution centre as one of the key risk mitigation practices in a construction supply chain.
3.3 An IoT-based risk monitoring system for managing cold supply chain risks
Tsang et al. (2018) propose an Internet of Things-based risk monitoring system (IoTRMS), which is aimed at controlling product quality and occupational safety risks in the cold chain. This system involves the integration of sensor network, cloud database and fuzzy logic algorithm to collect and analyse the product degradation risk and cold-associated occupational risk (e.g. accidents and injuries in the extreme cold environment) in different entities in the cold chain. The proposed intelligent system involves risk monitoring by means of the IoT application and artificial intelligence techniques. Facilitated by IoTRMS, the risk assessment and identification can be effectively established, so as to assure the product quality and appropriate occupational safety management in the cold chain environment.

3.4 A fuzzy-based House of Risk assessment method for manufacturers in global supply chains
Ma and Wong (2018) propose a fuzzy-based House of Risk assessment method for manufacturers to model risks existing in global supply chains. In order to improve the modelling precision and enable the modelling approach to reflect the real situation in terms of qualitative decision making, they apply the fuzzy logic modelling approach rather than the traditional deterministic House of Risk modelling approach. Based on their case study of a leading manufacturer in small household electronic appliances, they find that the fuzzy logic modelling approach can influence the inputs the risk events, risk agents and its occurrence. Moreover, this approach would be able to prioritise the risk agents, which benefit in deciding the proactive decisions.

4. Risk mitigation modelling
4.1 Using put option contracts in supply chains to manage demand and supply uncertainty
Luo et al. (2018) study the optimal ordering policy for a manufacturer and the optimal production policy for the corresponding supplier. Based on a supply chain model with one component supplier and one end-product manufacturer with the existence of a spot market, they study the advantages of both centralised and decentralised model with put option contracts. The study finds that put option can benefit the manufacturer’s order as well as the supplier’s production. Risks can be more effectively managed, and meanwhile higher profits can be obtained. In addition, the authors find that a single put option contract is not suitable for this supply chain model. They also demonstrate the conditions for achieving further improvement.

4.2 Minimising the risk of seaport operations efficiency reduction affected by vessel delay
This paper studies the risk of vessel arrival delay to the operations efficiency of a seaport terminal. In a traditional modelling approach, vessel arrival time is usually assumed to be deterministic. However, according to this paper, vessel arrival delay is common in the shipping industry. The authors propose a conditional probability modelling approach to capture the risk of vessel arrival delay. The study finds that by considering vessel arrival delay in berth allocation problems, the impacts of these problems on the operations efficiency can be minimised significantly.

4.3 Managing bioethanol supply chain resilience: a risk-sharing model to mitigate yield uncertainty risk
Ye et al. (2018) study the decision-making behaviour of bioethanol manufacturers and cassava planting farmers on the cooperation of contract farming scheme. They consider and conduct analysis based on two decision models – centralised and decentralised approaches – and propose a risk-sharing model to coordinate the two parties. The study finds that use
of the risk-sharing model helps to mitigate the yield uncertainty risk, while improving the 
resiliency of the cassava bioethanol supply chain in an environment of yield and demand 
uncertainties. They further categorise different conditions which may benefit the cooperation 
in both centralised and decentralised approaches.

5. Reviews in SCRM

5.1 Strategies and effective decision making against terrorism affecting SCRM and 
security: a novel combination of triangulated methods
Khan et al. (2018) propose a research model related to risk management strategies and 
effective decision making in the context of terrorism risks in the supply chain. To construct 
the research model they adopt a triangulated approach comprising a systematic literature 
review, text mining and network analysis. By reviewing and text mining 64 research 
articles, they develop a strategies and decision making against terrorism model. The model 
provides new insights for managers and academics so that they might have in-depth 
understanding about the key themes of decision making in the area of terrorism risk and 
security in supply chains.

5.2 Procurement risk management under certainty: a review
Hong et al. (2018) is a review paper on SCRM and procurement risk management from 1995 
to 2017. The authors have reviewed a total of 156 papers in several major databases, 
including Science Direct, Emerald, Scopus, Springer and Google Scholar, with the keywords 
risk management, supply chain management, supply risk, procurement, contract, and 
sourcing. They categorise the papers into five main risks and discuss seven major future 
challenges in the field of study.

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terrorism affecting supply chain risk management and security: a novel combination of 


Risk management and firm performance: the moderating role of supplier integration

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Abstract
Purpose – The purpose of this paper is to scrutinize the performance effects of supply chain risk management (SCRM). Besides financial performance, two aspects of operational performance are examined: operational efficiency and flexibility. Moreover, the authors explore the moderating role of supplier integration in the relationship between SCRM and operational performance.
Design/methodology/approach – A survey-based methodology was adopted. Based on the data from an international survey, this study applied the structural equation modeling and latent moderated structural equations approach to test the hypotheses.
Findings – The results indicate that SCRM positively influences both operational efficiency and flexibility, and has an indirect effect on financial performance. In addition, supplier integration enhances the impact of SCRM on operational flexibility, but does not moderate the relationship between SCRM and operational efficiency.
Originality/value – This study extends the existing literature by providing a comprehensive analysis of the performance effects of SCRM. It also provides managerial insights on both risk management and supplier integration.
Keywords Financial performance, Supply chain risk management, Supplier integration, Operational flexibility, Operational efficiency, Information processing theory
Paper type Research paper

1. Introduction
Modern supply chains operate in the complex and rapidly changing environment (Chen et al., 2013; Wiengarten et al., 2017). Meanwhile, firms apply increasingly sophisticated operations practices (e.g. lean manufacturing, rapid responsiveness and global outsourcing) to gain competitive advantage (Blome and Schoenherr, 2011; Kauppi et al., 2016). The fast-changing environment and firms’ complicated operational strategies together contribute to a higher level of supply chain risks. As a result, supply chain risk management (SCRM), which is defined as the identification and management of risks in the supply chain through coordinated approaches (Kauppi et al., 2016; Jüttner et al., 2003), is widely adopted by firms to cope with increasing risks (Lavastre et al., 2014; Manuj et al., 2014; Kauppi et al., 2016). Prior theoretical studies have suggested that firms can gain performance benefit through the implementation of SCRM (Narasimhan and Talluri, 2009; Thun and Hoenig, 2011; Manuj et al., 2014). The main
arguments in the extant literature are that SCRM is beneficial to firms’ financial performance by lowering operations accidents and preventing supply chain disruptions (Ritchie and Brindley, 2007; Narasimhan and Talluri, 2009; Thun and Hoenig, 2011; Manuj et al., 2014). However, the implementation of SCRM generally requires up-front investment and additional costs for excess inventories, extra capabilities, back-up suppliers and alternative transportation modes (Premkumar et al., 2005; Tang, 2006; Colicchia and Strozzi, 2012; Bode and Wagner, 2015; Kauppi et al., 2016), which may weaken financial performance. To our best knowledge, there is a dearth of empirical evidence on how SCRM practices actually influence financial performance. Therefore, this paper aims to explore the links between SCRM and financial performance.

In the extant literature, most scholars focus on the effect of SCRM on operational performance. Previous studies have widely recognized operational performance as a multi-dimensional construct. For example, Kauppi et al. (2016) show that risk management along the supply chain is positively related to five aspects of operational performance including quality, delivery, flexibility, cost and customer service. Operational efficiency and operational flexibility, which may compete for firm’s limited resources (e.g. labor, capital, etc.) and require different organizational configurations (e.g. operating processes, organizational structure, etc.) (Ebben and Johnson, 2005), are regarded as contradictory aspects of operational performance and have attracted great attention (Adler et al., 1999; Ebben and Johnson, 2005; Kortmann et al., 2014). On the one hand, firms attempt to profit from a lower cost by maintaining high efficiency (Ebben and Johnson, 2005; Eisenhardt et al., 2010). On the other hand, flexibility is critical for firms to adapt to the ever-changing environment and to satisfy diverse customer needs (Nadkarni and Narayanan, 2007; Eisenhardt et al., 2010). While previous studies have evidenced the positive effects of SCRM on different aspects of operational performance (e.g. cost, delivery, flexibility, quality, etc.) (Thun and Hoenig, 2011; Lavastre et al., 2014; Kauppi et al., 2016), the influence of SCRM on both operational efficiency and flexibility has not been investigated simultaneously. Thus, this paper intends to establish the relationship between SCRM and the two aspects of operational performance. Overall, the first research question of this study is:

**RQ1.** What are the effects of SCRM on firm performance, including both financial performance and operational performance?

The implementation of SCRM relies on coordination and collaboration between the focal firm and its suppliers to gain rich real-time upstream information. Prior studies have indicated the significant role of supplier relationship in the implementation of SCRM (Chen et al., 2013; Kauppi et al., 2016; Lavastre et al., 2014; Li et al., 2015; Zeng and Yen, 2017; Zsidisin and Smith, 2005). For example, Wiengarten et al. (2016) suggest that SCRM complements with supply chain integration in the weak rule of law environments to enhance firm performance. Li et al. (2015) highlight that joint risk management practices with suppliers contribute to the improvement of performance. This paper focuses on supplier integration, which indicates the coordination and collaboration practices with suppliers (Das et al., 2006; Flynn et al., 2010; Shou et al., 2017). Supplier integration provides external linkages for the focal firm to access supply chain information and improves the firm’s information processing capability through joint information sharing actions (Flynn et al., 2010; Wong et al., 2011). Since SCRM is an information intensive process (Manuj and Mentzer, 2008), supplier integration is supposed to improve the effectiveness of SCRM. Therefore, this study attempts to analyze the moderating effect of supplier integration on the relationship between SCRM and operational performance. The second research question is:

**RQ2.** How does supplier integration influence the performance effect of SCRM?

This study applies information processing theory (IPT) to crystallize the relationship between SCRM and performance outcomes, and the moderating effect of supplier
integration. IPT indicates that an organization can cope with uncertainty and achieve superior performance through reducing information processing requirements or increasing information processing capability (Galbraith, 1973; Premkumar et al., 2005). We argue that SCRM is an information intensive process which contributes to the improvement of performance outcomes, and should complement with supplier integration to access accurate and timely supply chain information and enhance information processing capabilities. An international survey was utilized to measure the relevant constructs and structural equation modeling (SEM) was used to test the hypothesized relationships. We find that SCRM has direct effects on operational performance and indirectly influence on financial performance. In addition, supplier integration shows different moderating effects on the relationship between SCRM and operational flexibility/efficiency. The contributions of this study are three-fold. First, it clarifies the performance effects of SCRM based on empirical evidence. Second, it provides an in-depth understanding on the relationship between SCRM and the two dimensions of operational performance (i.e. efficiency and flexibility). Last but not least, this study confirms the role of supplier integration in the effectiveness of SCRM and further supports the standpoints of IPT.

The rest of this paper is organized as follows. Section 2 introduces the theoretical background and hypotheses development. The research method, data analysis and results are presented in Sections 3 and 4. In Section 5, both theoretical and managerial implications are discussed. The last section concludes this study.

2. Theoretical background and hypotheses development

2.1 SCRM and firm performance

SCRM refers to focal firm’s activities to identify and manage risks associated with the supply chain through a coordinated approach (Jüttner et al., 2003). It includes “the integrated processes of identification, analysis and either acceptance or mitigation of uncertainty and risk in the supply chain” (Wiengarten et al., 2016, p. 364). We speculate that SCRM promotes financial performance. Financial performance indicates how well a firm can utilize its assets in generating profits (Wagner et al., 2012). Companies’ financial performance may be threatened by various supply chain risks, which “disrupt the information, material or product flow from original suppliers to the delivery of the final product to the ultimate end-user” (Peck, 2006). Kleindorfer and Saad (2005) mention two categories of risks affecting supply chain management: risks associated with supply and demand coordination, and disruption risks such as natural disasters, strikes and economic disruptions. Particularly, the increasing environmental uncertainty and supply chain complexity make companies vulnerable to risks (Bode and Wagner, 2015). Once the risk events occur, the firm will suffer damage to businesses while the remediation afterwards results in additional costs. In this case, financial performance cannot be ensured. SCRM practices can help reduce the loss through risk prevention and control, thereby leading to superior financial performance (Papadakis, 2006; Ritchie and Brindley, 2007). Hence, we propose the following hypothesis:

**H1.** SCRM is positively associated with financial performance.

Some studies have argued that SCRM contributes to operational performance such as lower operational loss or faster response (Thun and Hoenig, 2011; Manuj et al., 2014). This study scrutinizes two aspects of operational performance, i.e. operational efficiency and flexibility. From the perspective of IPT, uncertainty indicates the “difference between the amount of information required to perform a task and the amount of information already possessed by the organization” (Galbraith, 1973, p. 5), and therefore, the firm needs to gather and process information to cope with environmental uncertainty and achieve high levels of performance. In the context of supply chain, the information is concerned with inventory, logistics,
quality, quantity, technology, market, politics, monetary issues and the like (Fan et al., 2017). The information about demand, supply and production is highly complex, ambiguous and uncertain. Fan et al. (2017) point out that supply chain risk events always happen randomly, discretely, inevitably and continuously, which deteriorate firm performance. We argue that SCRM practices including risk preventing, detecting, responding and recovering can act as routines for companies to gather and process supply chain information. SCRM practices as information processing systems, and confirm that SCRM practices help mitigate uncertainty and ambiguity (Fan et al., 2017). The efficient information processing capability is beneficial to the improvement of operational efficiency and flexibility (Kauppi et al., 2016).

Operational efficiency is more easily achieved in a highly stable and controlled environment with prescribed quality and predictable demand (Maffei et al., 1993). Internal and external uncertainties are identified as key obstacles, which impede the realization of operational efficiency (Ebben and Johnson, 2005). The lack of information and faulty decisions will result in time and cost losses. Through mechanisms such as buffering strategies, contingency planning and referable procedures, companies can establish a reliable environment in which production activities operate with lower operational costs and shorter lead time (Ebben and Johnson, 2005). Meanwhile, a firm’s operational efficiency highly relies on its routines and capabilities (Lam et al., 2016). SCRM practices equip the firm with the ability to figure out and control potential risk factors in manufacturing processes and in the supply channel (Narasimhan and Talluri, 2009). The improved information processing capability through SCRM practices also helps reduce errors, avoid rework and thus leads to better delivery speed and higher efficiency (Fan et al., 2017). In turn, the inefficient SCRM practices may lead to resource waste and time losses. Once risk events such as demand fluctuations, supply shortage or production interruption occur, companies have to put extra time and cost into coordination and operation. In such cases, neither time-based nor cost-based efficiency can be guaranteed.

Operational flexibility (a.k.a. manufacturing flexibility) (Koste et al., 2004; Patel et al., 2012) is “a measure of a firm’s ability to respond to market demands by switching from one product to another through coordinated policies and actions” (Nemetz and Fry, 1988, p. 629). SCRM practices can improve operational flexibility by solving information-related problems. Due to the changing and competitive environment, companies are required to keep operational flexibility to adapt to customized requirements (Patel, 2011). Kauppi et al. (2016) indicate that one main method for risk management practices is buffering strategy. The companies adopt flexible production processes, alternative transportation modes, and multiple and back-up suppliers to reduce information needs in the competitive environment (Maffei et al., 1993; Bode et al., 2012). Manufacturers producing a variety of products and volumes rely on these buffers to deal with supply and demand uncertainty, so that they can respond to customers’ requirements in a flexible way. Moreover, strict risk management planning, specialized task forces, clear responsibilities and other risk management practices can enhance companies’ information processing capability and problem-solving capability. Quick decision making based on existing information helps the companies respond to contingencies rapidly and timely. The excellent information processing capability is always linked to increased responsiveness (Williams et al., 2013) and improved flexibility (Lummus et al., 2005). Therefore, we propose the hypothesis as follows:

\[ \text{H2. SCRM is positively associated with (a) operational efficiency and (b) operational flexibility.} \]

Operational efficiency and flexibility are conjectured to promote financial performance. Prior studies have discussed that volume flexibility, delivery speed and delivery dependability contribute to the growth in sales, return on sales (ROS) and return on investment (Vickerya and Marklandb, 1997). Droge et al. (2004) have confirmed the positive
effects of speed and efficiency on market share and financial performance. In addition, Elgazzar et al. (2012) analyze how supply chain performance like responsiveness, agility and cost links with financial performance like sales and return on assets. Yu et al. (2012) find in their survey that operational performance yields greater customer satisfaction and financial performance by providing quality products to satisfy customer needs and reducing delivery costs and serving costs. Indeed, operational efficiency and flexibility exhibit firms’ competitive capabilities in offering diversified products with lower cost and shorter lead time (Ebben and Johnson, 2005; Kortmann et al., 2014). Firms can fetch more orders by quickly responding to changing customer demand and satisfying customer needs (Yeung, 2008; Shrikant and Ravi, 2017). In other words, operational flexibility leads to increasing market share growth, sales and revenues. Moreover, operational efficiency enables the firm to deliver the orders in cost-saving and time-saving way, which ensures the orders to be profitable (Liu and Lai, 2016). Therefore, the firms with high levels of efficiency and flexibility are more likely to gain sales, accumulate earnings and attain high profit. Hence, we propose the following hypothesis:

\[ H3. \] The firm’s (a) operational efficiency and (b) operational flexibility are positively associated with financial performance.

2.2 The moderating role of supplier integration

As proposed by prior studies, the implementation of SCRM relies on the integrative relationship between focal firm and its suppliers (Chen et al., 2013; Li et al., 2015; Kauppi et al., 2016; Wiengarten et al., 2016). Supplier integration indicates the coordination and collaboration practices with suppliers (Das et al., 2006; Flynn et al., 2010). The term integration “essentially represents a structural and relational characteristic of a given organization or between organizations” (Barki and Pinsonneault, 2005, p. 166). Specifically, Das et al. (2006) suggest several structural characteristics for supplier integration, such as electronic data interchange, applications software and web-based integration systems. Additionally, relational characteristics in forms of collaboration and joint problem solving also indicate high levels of supplier integration (Gimenez and Ventura, 2005; Cagliano et al., 2006; Flynn et al., 2010; Shou et al., 2017). Generally speaking, supplier integration includes the aspects of information sharing, collaboration, joint decision making and system coupling (Shou et al., 2017).

In this paper, we argue that supplier integration can enhance the impact of SCRM on operational efficiency and flexibility. From the perspective of IPT, SCRM is an information intensive process, while supplier integration provides channels for external information acquisition, and enhances the firm’s information processing capability. First, supplier integration serves as external routines for the companies to collect accurate supply chain information (Wong et al., 2011). Information sharing with suppliers improves supply chain visibility and responsiveness, and is regarded as one key enabler for the effectiveness of SCRM practices (Christopher and Lee, 2004; Ritchie and Brindley, 2007). The adequate, timely and reliable internal and external information will complement with risk management practices and result in a higher level of operational efficiency and flexibility. Second, in the integrative relationship, the focal firm and its suppliers collaborate through risk and revenue sharing mechanism. It implies that suppliers can share positive outcomes if they put efforts into SCRM practices (Fan et al., 2017). Thus, the effectiveness and efficiency of risk information gathering and processing can be ensured. Third, the focal firm and its suppliers make decisions jointly when they engage in collaborative and integrative relationship (Flynn et al., 2010). Joint decision-making mechanisms improve the firm’s information processing capabilities, particularly in complex and uncertain environments. Enhanced information processing capabilities enable the focal firm to operate businesses in
an efficient way and respond to external environment in a flexible way. Therefore, we propose the following hypotheses:

- **H4a.** The level of supplier integration positively moderates the relationship between SCRM and operational efficiency.
- **H4b.** The level of supplier integration positively moderates the relationship between SCRM and operational flexibility.

Figure 1 presents the conceptual model of this study.

### 3. Research method

#### 3.1 Sample

In order to test the proposed hypotheses, this study used data collected through the sixth round International Manufacturing Strategy Survey (IMSS). The IMSS is a global survey executed by a research network of operations management scholars and manufacturing industry practitioners and completed by plant managers from manufacturing companies. The objective of IMSS is to establish a common database for the study of manufacturing practices and supply chain strategies. The IMSS is a mature and comprehensive international survey, which was originally developed in 1992 and was conducted every four to five years. The IMSS has been utilized by plenty of high-quality research publications in several research fields such as operations management and strategic management (e.g. Cheng et al., 2016; Demeter et al., 2016; Kauppi et al., 2016; Wiengarten et al., 2016).

The data used in this study were collected in 2013–2014. The local research groups in each country applied a centrally coordinated and rigorous procedure to collect data. A double parallel translation or back-translation method was strictly used to translate IMSS questionnaire into local languages. The respondents were contacted by e-mail and telephone call. Finally, 931 valid questionnaires were collected from 22 countries, with an aggregate response rate of 36 percent. For this study, 652 usable samples shown in Table I were obtained after deleting samples with missing data in related items.

Non-response and late-response bias were checked and controlled through a uniform protocol that each local research group was required to follow. The coordinators in each country compared the difference of size, industry, sales or proprietary structure between respondents and non-respondents and between early and late respondents by use of secondary data or questionnaire items. Evidence of non-response or late-response bias was not found in any of the cases (Cheng et al., 2016). We also checked common method bias with Harman’s single factor test. The results reveal five distinctive factors with eigenvalues above 1.0, of which the first factor explained 29.9 percent of the common variance and is not
Further, confirmative factor analysis was applied to test Harman’s single factor model. The model fit indices ($\chi^2/df = 16.578$, CFI = 0.567, TLI = 0.505, RMSEA = 0.155, SRMR = 0.124) were all worse than the recommended threshold, which indicate that the single factor model is not acceptable. Thus, common method bias is not a serious concern in this study.

3.2 Measures

Researchers have measured SCRM from a process perspective. For example, Sinha et al. (2004) provide a methodology to mitigate supplier risks through risk identification, risk assessment, solutions planning and implementation, failure modes and effect analysis, and continuous improvement. Kleindorfer and Saad (2005) focus on the joint activities of risk assessment and risk mitigation. Sodhi et al. (2012) summarize four elements for managing supply chain risks, including risk identification, risk assessment, risk mitigation and responsiveness to risks. Further, Kırımlı and Erol (2017) refine the processes into risk identification, risk measurement, risk evaluation, risk mitigation and the proposed procedure, and risk monitoring and control. Generally, the measurement of SCRM includes the activities of preventing, detecting, responding and recovering risks.

Financial performance is measured by sales and ROS (Wagner et al., 2012; Zhou et al., 2014). Operational efficiency indicates cost and time savings to maximize the ratio of output to input. Kortmann et al. (2014) divide operational efficiency into cost-based dimension (e.g. manufacturing costs) and time-based dimension (e.g. manufacturing lead time and delivery speed). Accordingly, this study measures operational efficiency as unit manufacturing cost, ordering costs, manufacturing lead time and procurement lead time.

<table>
<thead>
<tr>
<th>Demographic dimension</th>
<th>n</th>
<th>%</th>
<th>Demographic dimension</th>
<th>n</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Europe</td>
<td>320</td>
<td>49.07</td>
<td>Firm size</td>
<td>302</td>
<td>46.32</td>
</tr>
<tr>
<td>Belgium</td>
<td>18</td>
<td>2.76</td>
<td>Small (&lt; 250)</td>
<td>120</td>
<td>18.40</td>
</tr>
<tr>
<td>Denmark</td>
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<td>Medium (250–500)</td>
<td>230</td>
<td>35.28</td>
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<tr>
<td>Finland</td>
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<td>4.14</td>
<td>Large (&gt; 500)</td>
<td>230</td>
<td>35.28</td>
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<tr>
<td>Germany</td>
<td>9</td>
<td>1.38</td>
<td>Total</td>
<td>652</td>
<td>100.00</td>
</tr>
<tr>
<td>Hungary</td>
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<td>5.67</td>
<td>Industry (ISIC code)</td>
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<td>100.00</td>
</tr>
<tr>
<td>Italy</td>
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<td>3.83</td>
<td>25</td>
<td>204</td>
<td>31.29</td>
</tr>
<tr>
<td>The Netherlands</td>
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<td>5.37</td>
<td>26</td>
<td>84</td>
<td>12.88</td>
</tr>
<tr>
<td>Norway</td>
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<td>27</td>
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<td>17.48</td>
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<tr>
<td>Portugal</td>
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<td>28</td>
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<td>Romania</td>
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<td>29</td>
<td>67</td>
<td>10.28</td>
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<tr>
<td>Slovenia</td>
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<td>2.61</td>
<td>30</td>
<td>29</td>
<td>4.45</td>
</tr>
<tr>
<td>Spain</td>
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<td>2.76</td>
<td>Total</td>
<td>652</td>
<td>100.00</td>
</tr>
<tr>
<td>Sweden</td>
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<tr>
<td>Switzerland</td>
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<td>2.45</td>
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<td>Asia</td>
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<td>China</td>
<td>87</td>
<td>13.34</td>
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<tr>
<td>India</td>
<td>68</td>
<td>10.43</td>
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<td></td>
<td></td>
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<tr>
<td>Japan</td>
<td>71</td>
<td>10.89</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Malaysia</td>
<td>10</td>
<td>1.53</td>
<td></td>
<td></td>
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<tr>
<td>Taiwan</td>
<td>22</td>
<td>3.37</td>
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<tr>
<td>America</td>
<td>74</td>
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<td>Brazil</td>
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<td>4.14</td>
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<td></td>
</tr>
<tr>
<td>Canada</td>
<td>17</td>
<td>2.61</td>
<td></td>
<td></td>
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<tr>
<td>USA</td>
<td>30</td>
<td>4.60</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Total</td>
<td>652</td>
<td>100.00</td>
<td></td>
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</tr>
</tbody>
</table>

Table I. Sample overview
(Yeung, 2008; Kortmann et al., 2014). Operational flexibility indicates the responsiveness capability to unanticipated situations and dynamically changing environments. There are many dimensions to measure flexibility, including labor, machine, material handling, routing, volume and mix flexibility. Zhang et al. (2003) advocate that process flexibility (labor, machine, material handling and routing) should be distinguished from operational flexibility (volume and mix), while the former indicates flexible competence, and the latter implies flexible capability. Besides, Koste et al. (2004) emphasize mix, new product and modification flexibility as higher-level flexibility dimensions due to their competitive importance for the market. The measurement of operational flexibility in this study focuses on volume flexibility, mix flexibility and product customization ability.

Supplier integration refers to collaborative and coordinative activities between the firm and its suppliers (Das et al., 2006; Flynn et al., 2010). Shou et al. (2017) elaborate integration from the structural and relational aspects. The structural integration indicates formal communication and information sharing, while the relational integration is concerned with joint actions and collaborative attitudes. Besides, Kim and Lee (2010) also emphasize the compatible communication and production systems between supply chain partners. Based on prior studies (Gimenez and Ventura, 2005; Flynn et al., 2010; Kim and Lee, 2010; Shou et al., 2017), this study measures supplier integration in terms of information sharing, collaboration, joint decision making and system coupling.

All the above constructs, including SCRM, financial performance, operational efficiency, operational flexibility and supplier integration, were measured by five-point Likert scales. Besides, this study included two control variables (i.e. firm size and industry). Firm size is included since larger firms tend to have more resources and better capabilities to implement management practices and can gain economies of scale from their implementation (Shou et al., 2017). This study also controls for industry type (Li et al., 2015; Wei et al., 2017).

3.3 Reliability and validity

We conducted confirmatory factor analysis (CFA) using Mplus 7.4 to validate the measures of the constructs in our research. The CFA results are shown in Table II. The goodness of fit indices for CFA measurement model are $\chi^2/df = 2.244$, RMSEA = 0.044, CFI = 0.968, TLI = 0.961 and SRMR = 0.028. These indices are all better than the recommended threshold, which indicate a reasonably good fit (Hu and Bentler, 1999). Besides, Cronbach’s $\alpha$ for each construct was calculated by SPSS 22.0. The results confirm internal consistency reliability of the five constructs.

We demonstrate construct validity in terms of content validity, convergent validity and discriminant validity. First, developed by a team of senior researchers and extracted from solid operations literature, the sixth round IMSS adopted scales tested by prior research and earlier versions of the survey, which guarantees the content validity of the items. Second, all constructs were measured by multi-item scales. The CFA results show that all factor loadings are above 0.50 and the $t$-values are all larger than 10.0. The factor loadings all exceed twice the value of their associated standard errors. A composite reliability (CR) value being greater than 0.70 is recommended (Shah and Goldstein, 2006), while a value between 0.60 and 0.70 is also acceptable provided that other indicators of reliability are good (Hair et al., 2010). The CR values of all the constructs are greater than 0.70 except financial performance (with a value of 0.695). The estimates for average variance extracted (AVE) for SCRM, financial performance, operational flexibility and supplier integration are all above 0.50. The estimate for operational efficiency is 0.453, which is above 0.40 and still acceptable (Menor et al., 2007). In addition, all AVE estimates are less than the corresponding CR values (Hair et al., 2010). Given the above results, the degree of convergent validity is acceptable. Third, correlations of the constructs are calculated. As shown in Table III, the square root of AVE value for each construct is larger than any corresponding correlation coefficient.
We also compared the unconstrained model with the correlations between each two constructs allowed to vary freely and the constrained model with the correlations constrained to 1. The significant differences in $\chi^2$ provide further evidence for discriminant validity (O'Leary-Kelly and Vokurka, 1998).

<table>
<thead>
<tr>
<th>Construct and items</th>
<th>Factor loadings (standardized)</th>
<th>$t$-value</th>
<th>SE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply chain risk management</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RM1 Preventing operations risks (e.g. select a more reliable supplier, use clear safety procedures, preventive maintenance)</td>
<td>0.742</td>
<td>35.720</td>
<td>0.021</td>
<td>0.550</td>
</tr>
<tr>
<td>RM2 Detecting operations risks (e.g. internal or supplier monitoring, inspection, tracking)</td>
<td>0.847</td>
<td>55.794</td>
<td>0.015</td>
<td>0.718</td>
</tr>
<tr>
<td>RM3 Responding to operations risks (e.g. back-up suppliers, extra capacity, alternative transportation modes)</td>
<td>0.823</td>
<td>50.162</td>
<td>0.016</td>
<td>0.677</td>
</tr>
<tr>
<td>RM4 Recovering from operations risks (e.g. task forces, contingency plans, clear responsibility)</td>
<td>0.800</td>
<td>45.314</td>
<td>0.018</td>
<td>0.639</td>
</tr>
<tr>
<td>Financial performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FP1 Sales compared to the three years ago</td>
<td>0.721</td>
<td>10.178</td>
<td>0.071</td>
<td>0.519</td>
</tr>
<tr>
<td>FP2 ROS compared to the three years ago</td>
<td>0.739</td>
<td>10.233</td>
<td>0.072</td>
<td>0.546</td>
</tr>
<tr>
<td>Operational efficiency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OE1 Unit manufacturing cost</td>
<td>0.619</td>
<td>18.470</td>
<td>0.034</td>
<td>0.383</td>
</tr>
<tr>
<td>OE2 Ordering costs</td>
<td>0.676</td>
<td>21.263</td>
<td>0.032</td>
<td>0.456</td>
</tr>
<tr>
<td>OE3 Manufacturing lead time</td>
<td>0.694</td>
<td>22.983</td>
<td>0.030</td>
<td>0.482</td>
</tr>
<tr>
<td>OE4 Procurement lead time</td>
<td>0.700</td>
<td>23.160</td>
<td>0.030</td>
<td>0.490</td>
</tr>
<tr>
<td>Operational flexibility</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OF1 Volume flexibility</td>
<td>0.742</td>
<td>25.283</td>
<td>0.029</td>
<td>0.551</td>
</tr>
<tr>
<td>OF2 Mix flexibility</td>
<td>0.809</td>
<td>28.039</td>
<td>0.029</td>
<td>0.655</td>
</tr>
<tr>
<td>OF3 Product customization ability</td>
<td>0.543</td>
<td>16.056</td>
<td>0.034</td>
<td>0.294</td>
</tr>
<tr>
<td>Supplier integration</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI1 Sharing information with key suppliers (about sales forecast, production plans, order tracking and tracing, delivery status, stock level)</td>
<td>0.758</td>
<td>37.584</td>
<td>0.020</td>
<td>0.574</td>
</tr>
<tr>
<td>SI2 Developing collaborative approaches with key suppliers (e.g. supplier development, risk/revenue sharing, long-term agreements)</td>
<td>0.845</td>
<td>52.630</td>
<td>0.016</td>
<td>0.714</td>
</tr>
<tr>
<td>SI3 Joint decision making with key suppliers (about product design/modifications, process design/modifications, quality improvement and cost control)</td>
<td>0.816</td>
<td>46.785</td>
<td>0.017</td>
<td>0.666</td>
</tr>
<tr>
<td>SI4 System coupling with key suppliers (e.g. vendor managed inventory, just-in-time, Kanban, continuous replenishment)</td>
<td>0.668</td>
<td>26.712</td>
<td>0.025</td>
<td>0.446</td>
</tr>
</tbody>
</table>

**Notes:** The square root of AVE is in the diagonal. *, **Significant at the 0.05 and 0.01 levels, respectively.

(Fornell and Larcker, 1981).
3.4 Measurement equivalence

Since we used cross-sectional data to test the proposed hypotheses, the measurement equivalence across regions should be assessed. We analyzed the measurement equivalence in terms of calibration, translation and metric equivalence (Mullen, 1995). Calibration equivalence can be ensured when the measurement scales used are standardized Likert scales. In this survey, five-point Likert scales were applied to measure each construct. Furthermore, translation equivalence of all items is guaranteed as rigorous translation/back-translation processes were conducted during the execution of IMSS (Kauppi et al., 2016). Metric equivalence is “the equivalence in the scoring process or the way respondents in different countries answer the same question” (Mullen, 1995). A multi-group CFA was recommended to determine metric equivalence (Rungtusanatham et al., 2008; Patel et al., 2012). In order to test metric equivalence, we compared the fit of two models: one is a fully constrained model in which all factor loadings were constrained to be equal across Europe, Asia and America, and the other is an unconstrained model with freely estimated factor loadings across continents. The goodness fit indices for constrained model are $\chi^2/df = 1.733$, CFI = 0.942, TLI = 0.932 and RMSEA = 0.034, while the indices for unconstrained model are $\chi^2/df = 1.762$, CFI = 0.943, TLI = 0.929 and RMSEA = 0.034. The results indicate that the data from different continents fit both models well. Further, model comparison results show that the fit of constrained model is not significantly different from that of unconstrained model with $\Delta \chi^2/\Delta df = 1.339$ and $p = 0.124$. Thus, metric equivalence is confirmed.

4. Results

In this study, we used the SEM to test our proposed $H1$–$H3$, so that we can get the estimation of all hypothesized paths simultaneously. To test the moderating effects ($H4a$ and $H4b$), we applied the latent moderated structural (LMS) equations approach, which is competent when the moderator is a multi-item latent variable (Kelava et al., 2011). The LMS technique is a distribution-analytic approach, in which the non-normal distribution of the latent outcome variable is approximated with a finite mixture of normal distributions and the coefficients for the first-order and interaction effects are then estimated (Klein and Moosbrugger, 2000). Simulation studies show that LMS provides efficient and unbiased estimation of latent interaction effects (Hancock and Mueller, 2013; Patel et al., 2012). Besides, the LMS technique is regarded as superior to the multi-group approach since it does not require splitting the sample, which eliminates the risk of sequencing the moderating effect (Wiengarten et al., 2017). Mplus 7.4 was used to run the LMS approach to analyze the latent interaction effects generated by SCRM and supplier integration.

The standardized path coefficients and the $p$-values of the structural equation model for $H1$–$H3$ are presented in Table IV. The relative and absolute indices of model fit show that the SEM model fits well to the data ($\chi^2/df = 2.098$, CFI = 0.950, TLI = 0.941, RMSEA = 0.041, SRMR = 0.049). The standardized path coefficient for $H1$ (SCRM $\rightarrow$ financial performance) is 0.064 with $p$-value being 0.232, which indicates that SCRM has no significant direct effects on

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>SE</th>
<th>$p$-value</th>
<th>Estimate</th>
<th>SE</th>
<th>$p$-value</th>
<th>Estimate</th>
<th>SE</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply chain risk management</td>
<td>0.225***</td>
<td>0.046</td>
<td>0.000</td>
<td>0.317***</td>
<td>0.044</td>
<td>0.000</td>
<td>0.064</td>
<td>0.053</td>
<td>0.232</td>
</tr>
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<td>Operational flexibility</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm size</td>
<td>0.068</td>
<td>0.046</td>
<td>0.141</td>
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</tr>
</tbody>
</table>

Table IV. Results for path analysis

Notes: Industry dummies are not shown. Standardized estimates. *$p < 0.05$; ***$p < 0.001$
financial performance. Hence, \( H1 \) is not supported directly. The standardized path coefficient for \( H2a \) (SCRM \( \rightarrow \) operational efficiency) and \( H2b \) (SCRM \( \rightarrow \) operational flexibility) is 0.225 and 0.317, which are both significant at the level of 0.001. Thus, the results provide strongly support for \( H2a \) and \( H2b \). The standardized path coefficient for \( H3a \) (operational efficiency \( \rightarrow \) financial performance) and \( H3b \) (operational flexibility \( \rightarrow \) financial performance) is 0.223 and 0.111, which are significant at the level of 0.001 and 0.05 respectively. Therefore, both \( H3a \) and \( H3b \) are supported.

To further test the potential indirect effects of SCRM on financial performance through operational efficiency and flexibility, we conducted bootstrap analysis (Li et al., 2017; Preacher and Hayes, 2008). The results of bootstrap analysis for indirect effect are presented in Table V. The total indirect effect is 0.057 with the 95% confidence interval ranging from 0.027 to 0.094. The exclusion of 0 in the 95% confidence interval indicates the existence of significant indirect effect of SCRM on financial performance. As shown in Table V, the indirect effects through operational efficiency and flexibility are 0.034 and 0.024, respectively. The 95% confidence intervals for both operational efficiency and flexibility do not include 0 as well, which indicates the statistically significant indirect effects through both operational efficiency and flexibility. Hence, \( H1 \) is supported. To conclude, SCRM improves a firm’s financial performance indirectly via operational efficiency and flexibility.

To test \( H4a \) and \( H4b \), we adopted the LMS approach to estimate the latent interaction effects between supplier integration and SCRM. The moderating results are presented in Table VI. The results show that the interaction effect of SCRM and supplier integration on operational flexibility is significant with \( p \)-value being 0.011. Thus, supplier integration positively moderates the relationship between SCRM and operational flexibility. However, the interaction effect of SCRM and supplier integration on operational efficiency is not significant, with \( p \)-value being 0.549. It can be concluded that supplier integration does not show significant moderation effect on the SCRM-operational efficiency relationship. Therefore, \( H4a \) is not supported, whereas \( H4b \) is confirmed.

### Table V.

<table>
<thead>
<tr>
<th></th>
<th>Point estimate</th>
<th>Boot</th>
<th>SE</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>0.057</td>
<td>0.057</td>
<td>0.017</td>
<td>0.027</td>
<td>0.094</td>
</tr>
<tr>
<td>Operational efficiency</td>
<td>0.033</td>
<td>0.034</td>
<td>0.013</td>
<td>0.012</td>
<td>0.062</td>
</tr>
<tr>
<td>Operational flexibility</td>
<td>0.024</td>
<td>0.024</td>
<td>0.011</td>
<td>0.004</td>
<td>0.050</td>
</tr>
<tr>
<td>C1</td>
<td>-0.010</td>
<td>-0.010</td>
<td>0.017</td>
<td>-0.044</td>
<td>0.025</td>
</tr>
</tbody>
</table>

**Notes:** C1, contrast of the two indirect effects; BC, bias corrected; CI, confidence intervals. Number of bootstrap samples: 5,000

### Table VI.

<table>
<thead>
<tr>
<th></th>
<th>Operational efficiency</th>
<th></th>
<th>Operational flexibility</th>
<th></th>
<th>Financial performance</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
<td>( p )-value</td>
<td>Estimate</td>
<td>SE</td>
<td>( p )-value</td>
</tr>
<tr>
<td>Supply chain risk management</td>
<td>0.059</td>
<td>0.048</td>
<td>0.220</td>
<td>0.191**</td>
<td>0.064</td>
<td>0.003</td>
</tr>
<tr>
<td>Supplier integration</td>
<td>0.142**</td>
<td>0.048</td>
<td>0.003</td>
<td>0.117</td>
<td>0.065</td>
<td>0.071</td>
</tr>
<tr>
<td>Supply chain risk management × supplier integration</td>
<td>0.031</td>
<td>0.051</td>
<td>0.549</td>
<td>0.154*</td>
<td>0.060</td>
<td>0.011</td>
</tr>
<tr>
<td>Firm size</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

**Notes:** Industry dummies are not shown. Unstandardized estimates. \(* p < 0.05; \**p < 0.01\)
5. Discussion
5.1 Theoretical implications

Our research contributes to the risk management literature in three aspects. First, this study clarifies the performance effects of SCRM based on empirical evidence. The results indicate that SCRM has significant effect on financial performance even though the effect is not direct. The implementation of risk management may help reduce potential losses through risk prevention and control, and hence improve financial performance. However, SCRM practices indicate up-front investment in excess inventories, extra capabilities, product designs and human resources (Maffei et al., 1993; Bode et al., 2012), and also imply great efforts in planning, monitoring and recovering (Sodhi et al., 2012). The up-front investment and costs are supposed to weaken financial performance. Therefore, the direct relationship between SCRM and financial performance is not significant because the positive and negative effects could offset each other. Further, the results reveal that SCRM can indirectly promote financial performance through improving operational performance. Although previous studies have confirmed the positive effect of SCRM practices on operational performance (e.g. Lavastre et al., 2014; Kauppi et al., 2016; Fan et al., 2017), this paper extends the relevant research by revealing that the improvement of operational performance can ultimately lead to focal firm’s financial performance. Therefore, this study establishes the link between SCRM practices and financial performance and demonstrates the role of operational performance.

Second, this study focuses on two critical dimensions of operational performance (i.e. operational efficiency and operational flexibility), and crystalizes the relationship between SCRM and operational efficiency and flexibility through the lens of IPT. Previous studies point out that efficiency and flexibility are sometimes contradictory and hard to be realized simultaneously (Ebben and Johnson, 2005; Kortmann et al., 2014). The results of this study confirm that SCRM enhances both operational efficiency and flexibility. According to IPT, SCRM helps to provide a stable and reliable environment through buffering strategies, contingency planning and referable procedures, and reduces the information processing requirements from external environment. In addition, SCRM enhances information processing capability and problem-solving capability through the joint information sharing practices and operational buffers. Therefore, the firm can respond to upstream disruptions and customized demands timely and rapidly. The findings suggest that SCRM practices facilitate firms to meet diversified customer requirements in an efficient way, which enhances the understanding on the relationship between SCRM and operational performance.

Third, supplier integration, as an information processing mechanism, is identified to moderate the relationship between SCRM and operational performance. A few studies have emphasized the role of supplier integration, supplier collaboration and supplier relationships in risk management practices (Chen et al., 2013; Lavastre et al., 2014; Li et al., 2015; Wiengarten et al., 2016; Kauppi et al., 2016). Our research extends prior studies by revealing the differential moderating roles of supplier integration. Specifically, the results show that supplier integration positively moderates the relationship between SCRM and operational flexibility. However, supplier integration does not significantly moderate the SCRM-operational efficiency relationship. It can be asserted that the focal firm has different information processing requirements for achieving operational efficiency and flexibility. Particularly, operational flexibility denotes the ability for product customization, higher levels of product variety and rapid responsiveness and so on to meet diversified customer requirements (Eisenhardt et al., 2010). Thus, it is necessary to have more complicated and sophisticated information and associated higher information processing capability in order to realize operational flexibility (Adler et al., 1999). In contrast, operational efficiency emphasizes the cost- and time-saving orientations and aims at achieving higher equipment utilization, labor productivity and the overall productivity (Kortmann et al., 2014). As a
result, information required by operational efficiency is relatively simple and regular compared to the information required by flexibility. Therefore, the findings extend prior studies by revealing the different roles of supplier integration in complementing SCRM practices to realize operational efficiency and flexibility, and further support the theoretical standpoints of IPT.

5.2 Managerial implications
The results of our study also provide some managerial insights. First, this study suggests that the firm should put efforts in SCRM practices. Managers with low awareness of the increasing complexity and uncertainty may take risk management lightly, or they are not willing to invest in SCRM practices due to the up-front costs. However, in case of risk events, there could be huge loss for the firm. For example, BMW, the German automaker, had to shut down some plants and suffered a loss of profit due to its dependent supplier Bosch's inability to provide sufficient number of steering gears in 2017 (Boston, 2017). If BMW had back-up suppliers or had more supply information in advance, they would not suffer so much. The findings of this paper confirm that SCRM improves operational performance directly and promotes financial performance indirectly. We emphasize the importance of operational performance in the relationship between SCRM and financial performance. For firms pursuing financial benefits from SCRM practices, they are encouraged to first attach great importance to the improvement of operational efficiency and flexibility. With the increasing competition and differentiated demands, firms are required to provide diversified customer services in a cost- and time-saving way. Therefore, the firm should invest enough on the implementation of SCRM practices and the improvement of operational flexibility and efficiency.

In addition, our findings suggest that a high level of supplier integration enhances the effectiveness of risk management on operational flexibility. Some supplier information sharing strategies and technologies have been adopted by the industry to identify risks and provide precise supply information and customer expectations. For instance, Zaragoza Logistics Center in Spain is developing an estimated time of arrival predictor tool for shipments exported from China to Spain (Urciuoli, 2017) to speed up information circulation, which facilitates the focal firm's risk management and eventually helps improve operational flexibility. According to the findings of this study, it is suggested that firms that are implementing risk management invest in technologies, IT systems and inter-firm relationships to maintain better supplier integration and further improve the effectiveness of SCRM.

6. Conclusions
This study extends previous research on the relationship between SCRM and firm performance through the lens of IPT. Our results suggest that SCRM practices directly contribute to the improvement of operational efficiency and flexibility, and have indirect effect on financial performance. The findings clarify the performance effects of SCRM and enhance the understanding on the link between SCRM and firm performance. Moreover, this study incorporates the role of supplier integration in the implementation of risk management. By focusing on two aspects of operational performance, this study reveals that supplier integration significantly enhances the impact of SCRM on operational flexibility but does not moderate the SCRM-operational efficiency relationship due to the different information processing requirements for achieving operational efficiency and flexibility. Compared to the regular operations information required by operational efficiency, the information required by operational flexibility is more complicated and sophisticated. The results reveal the different roles of supplier integration in the effectiveness of SCRM and further support the standpoints of IPT. Thus, supplier integration practices (e.g. information sharing, IT technologies and systems) should be conducted by firms, so that they can deal with uncertainty and achieve better operational flexibility.
There are some limitations in this study, which also indicate further research directions. First, this study used cross-sectional data to test the proposed hypotheses. Longitudinal studies are suggested to investigate the evolitional patterns of risk management, supplier integration and firm performance. Second, our research aimed to identify how SCRM and supplier integration impact operational and financial performance, but did not consider other contextual factors. Indeed, there are different forms of risk, which may influence SCRM and supplier integration strategies. Further research could investigate the contingency effects of supply chain risks.

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Managing hazards of the make-buy decision in the face of radical technological change

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Abstract

Purpose – The purpose of this paper is to consider the management of hazards arising from the make-buy choice in the face of radical technological change. This sourcing choice can lead to distinctive exchange and hierarchical hazards. This study’s main interest is in investigating the research question “How can firms reduce those distinctive exchange and hierarchical hazards arising from the make-buy sourcing strategy when dealing with radical technological change?”

Design/methodology/approach – The author develops hypotheses that the in-house retention of outsourced component knowledge will likely reduce exchange hazards arising from the buy strategy choice. And prior exploratory technological experience will likely reduce hierarchical hazards arising from the make strategy choice. The author explores the US mountain bicycle industry from 1980 to 1992 to test the developed hypotheses. For endogeneity arising from the make-buy sourcing decision, the author uses Heckman’s two-stage switching regression model.

Findings – The major findings are that the in-house retention of outsourced component knowledge and prior exploratory technological experience is distinctive moderating factors improving performance of a buy strategy and a make strategy, respectively.

Originality/value – Since the extant literature tends to focus on which of the two sourcing strategies provides the greatest performance advantages in the face of radical technological change, there is a strong implication to suggest that if a firm performs poorly with one sourcing decision, the firm should switch to an alternative one. Different from the expositions of the literature, this study elevates the understanding regarding how firms can improve the performance of their current sourcing orientation rather than whether they should switch from one sourcing strategy to another.

Keywords Exchange hazards, Hierarchical hazards, Make or buy sourcing decision, Prior exploratory technological experience, Radical technological change, Retention of outsourced component knowledge

Paper type Research paper

Introduction

There has been growing interest in the relationship between radical technological change and the make-buy component sourcing decision and its impact on performance in the technology management literature (Grant, 1996; Kogut and Zander, 1992; Monteverde, 1995; Nickerson and Zenger, 2004; Powell et al., 1996; Spencer, 2003). To facilitate a better understanding of the subsequent theoretical arguments presented in this paper and the relevant literature, we provide the following illustration. Consider as the unit of analysis a product that is comprised of two components: C1 and C2. Two separate firms, A and B, produce this product. The product then faces a radical technological change in the market that significantly alters components C1 and C2 and the linkages between them. To address this new change, both firms A and B make C1 internally. However, while firm B employs “a make strategy” (i.e. makes C2 internally) and firm A employs “a buy strategy” (i.e. buys C2 through an arm’s-length market transaction).

Given this simple model, much of the technology management literature focuses on investigating which sourcing strategy provides greater performance advantages in the face of a radical technological change (Nickerson and Zenger, 2004; Williamson, 1985; Wolter and Veloso, 2008). Some scholars argue for a make strategy over a buy strategy (Grant, 1996;
Monteverde, 1995; Nickerson and Zenger, 2004; Park and Ro, 2013) while others argue for a buy strategy over a make strategy (Abecassis-Moedas and Benghozi, 2012; Balakrishnan and Wernerfelt, 1986; Harrigan, 1984; Powell et al., 1996; Spencer, 2003).

Given the conflicting arguments and findings regarding the performance benefits of the make-buy sourcing decision, another stream of the technology management literature investigates why firms find it difficult to switch to a new sourcing strategy, even if the new strategy provides greater performance advantages (than the current sourcing strategy) in the face of radical technological change (Amburgey and Miner, 1992; Halebian et al., 2006; Zollo et al., 2002). This literary stream’s main arguments are that once a firm selects a particular sourcing strategy, the firm’s personnel, resources, and routines will mature and develop and eventually become established around the selected strategy. Thus, once a firm chooses a specific sourcing strategy, it becomes difficult for the firm to switch to a new one (Amburgey and Miner, 1992; Zollo et al., 2002). And, due to heterogeneous organizational capabilities, different firms will make different sourcing decisions even when addressing the same technological change (Kapoor, 2013; Nickerson and Silverman, 2003). Given the high irreversibility of the sourcing decision, RQ1 is a very valuable one not only on account of its potential theoretical contribution to the literature, but also due to its potential contribution to managerial practice. Namely, this study investigates the different moderating factors that can improve the performance of firms whether they utilize a make strategy or a buy strategy.

There are some studies that attempt to provide moderating factors for the make-buy sourcing decision in the context of technological change, but much of this research is focused on long-term relationships existing between a firm and its supplier (Gulati, 1995; Hoetker, 2005). Since the research regarding moderating factors is still under-explored, this study considers two important moderating factors—the in-house retention of knowledge concerning outsourced components and prior exploratory technological experience.

Regarding the in-house retention of knowledge concerning outsourced components, the illustration provided in the Introduction serves as a reference. Some firms in pursuing a buy strategy focus on in-sourcing component C1 and outsourcing component C2, yielding both the design and production of C2 to an external supplier. Contrastingly, some firms that choose to outsource component C2, still retain in-house knowledge concerning C2. This contrasting situation is referred to as the in-house retention of knowledge concerning outsourced components. This in-house retention of outsourced component knowledge leads to heterogeneous capabilities in later integrating components C1 and C2, ultimately leading to performance heterogeneity.

Concerning prior exploratory technological experience, some firms may possess greater levels of previous experience dealing with, or creating, radical innovations. When a radical innovation hits the market, some firms may have already had prior technological experience with radical innovations; other firms may not have such experience. Those firms with prior experience dealing with radical innovations are likely to have more effective capabilities in integrating and reconfiguring C1 and C2 for the new radical innovation.

Given the existence of the unique advantages (or disadvantages) between the make vs buy strategy choice, this study’s overarching arguments are, first, that the retention of outsourced component knowledge is likely to compensate for the weakness of a buy strategy in dealing with radical technological changes, thereby improving the performance of firms selecting a buy strategy. Second, prior exploratory technological experience may compensate for the weakness of both a make strategy and a buy strategy. However, it is more likely to compensate for the weakness of a make strategy than a buy strategy, resulting in a more likely performance improvement of the make strategy than the buy strategy. The combination of the first and second arguments prompts us to conclude that the in-house retention of outsourced component knowledge and prior exploratory
technological experience can serve as distinctive moderating factors improving the performance of the buy strategy and the make strategy, respectively.

This study’s main contribution is to foster an initial understanding as to how firms pursuing a buy strategy and firms pursuing a make strategy can handle distinctive hazards arising from the make-buy sourcing choice in the face of a radical technological change. Since the extant literature tends to focus on which of the two sourcing strategies provides the greatest performance advantages in the face of radical technological change, there is a strong implication to suggest that if a firm performs poorly with one sourcing decision, the firm should switch to an alternative one. Different from the expositions of the literature, this study elevates the understanding regarding how firms can improve the performance of their current sourcing orientation rather than whether they should switch from one sourcing strategy to another.

Theory and hypothesis development

Radical technological change—US mountain bicycle gear shifting market

The defined meaning of radical technological change can be broad and obscure. For a better understanding of radical technological change, this study begins with describing the technological change as it happened in the US mountain bicycle gear shifting market between 1980 and 1992. In terms of structure and technology, the defined architecture of the mountain bicycle has been relatively stable for much of the last century. In 1985, index shifting technology was introduced to the mountain bicycle market. Before the advent of index shifting, bicycle riders often used subjective judgment and constantly adjusted a shifter lever in order to successfully shift the chain from one gear to another. In contrast, with each click of the shifter in an index shifting system, the derailleur aligned the chain automatically onto one of the evenly spaced freewheels (Bicycling, February 1986, pp. 154-156). This new technology was very appealing to the mountain bicycle market since it allowed riders to automatically change gears simply by pushing a shifter, providing enthusiasts with immediate high performance gear shifting to deal with highly uncertain and rugged terrain.

When gear shifting, the derailleur and freewheel (parts of the bicycle drive train) are key components, and are the most relevant components influencing shifting performance. With the introduction of index shifting technology, the inner designs of these two components were altered, in addition to the linkage between them. This new linkage was termed the chain gap. Without an optimized chain gap design, bicycles using an index shifting system are not able to provide premium shifting performance (Bicycling, March 1987, pp. 108-128) (Fixson and Park, 2008).

Historically, the shift to the new index shifting technology was competence destroying (i.e. radical technological change) since components and the linkages between components were dramatically different from the traditionally entrenched dominant non-indexed gear shifting technology. In dealing with this remarkable innovation, while most firms in the market chose to make derailleur components in-house, they also needed to choose whether to make or buy the partnering freewheel component.

Exchange hazards by a buy choice and hierarchy hazards by a make choice

Given the context that a new radical innovation hits a market entrenched in an older technological paradigm, the technology management literature develops arguments regarding the impact of the make vs buy component sourcing decision on performance benefits, but their arguments can contradictory. The literature draws on transaction cost economies (Williamson, 1985; Yan and Kull, 2015) and knowledge-based view (Nickerson and Zenger, 2004).
One group of researchers argues for a make strategy over a buy strategy by emphasizing exchange hazards arising from the buy strategy choice (Grant, 1996; Monteverde, 1995; Nickerson and Zenger, 2004; Park and Ro, 2013). Radical technological change would often render firms’ and suppliers’ capability obsolete (Tushman and Anderson, 1986). A firm and its supplier are likely to face high coordination problems such as formulating R&D goals (Armour and Teece, 1978) and disagreeing about proper technological approaches and processes (Argyres, 1995). These conditions require extensive communication between the firm and its supplier, very likely leading them to relationship-specific engineering efforts and investments. When few suppliers are available in the market due to such engineering efforts and investments, a supplier that is aware of a buying firm having few outsourcing choices can exploit the buyer’s dependence. Due to the uniqueness of a new technology, a supplier might charge excessive rents and take advantage of its buying partner if left unchecked by strict contracts and diligent monitoring. And, situations where suppliers exhibit strong opportunistic behaviors are called exchange hazards (Globerman, 1980; Masten, 1984).

A make strategy is comparatively advantaged in dealing with exchange hazards as its firm-specific information and communication channels and routines, combined with its dispute resolution mechanisms, help codify knowledge and facilitate its efficient dissemination and transformation. These firm-specific routines and dispute resolution mechanisms allow firms to efficiently avoid exchange hazards (Grant, 1996; Kogut and Zander, 1996; Monteverde, 1995). In contrast, a buy strategy is inherently inefficient in dealing with exchange hazards on account of its weak support of knowledge sharing and restricted safeguards against knowledge appropriation (Nickerson and Zenger, 2004). Thus, given the relative advantage of a make strategy over a buy strategy in dealing with exchange hazards, this group of researchers argues that firms with a make strategy are likely to outperform firms with a buy strategy in the face of radical technological changes.

In contrast, another group of researchers argues for a buy over a make strategy by highlighting hierarchical hazards arising from the make strategy choice (Abecassis-Moedas and Benghozi, 2012; Balakrishnan and Wernerfelt, 1986; Harrigan, 1984; Powell et al., 1996; Spencer, 2003). Although a make strategy allows firms to efficiently develop communication channels that help reduce exchange hazards (Kogut and Zander, 1996; Monteverde, 1995), constraints on the identification and acquisition of new external knowledge across organizational boundaries can develop from shared routines evolving from a firm’s past activities (Henderson and Clark, 1990; March and Simon, 1993; Nelson and Winter, 1982). By continuously employing a make strategy over time, firms cultivate specific communication channels and information filters that limit the breadth of knowledge that they can identify and incorporate (Henderson and Clark, 1990). The unique background of a firm and the competition over resources induce problem solvers to find solutions primarily with their own organizational knowledge and routines. Since their solution search is structured based on a make strategy, a firm may have difficulty in finding external knowledge that differs substantially from its existing knowledge stock. Such situations are deemed hierarchical hazards that give rise to difficulties for firms in acquiring external knowledge due to its established routines and structures formed around the make sourcing strategy.

In contrast, a buy strategy offers powerful incentives that allow individual firms and suppliers to exploit and enhance proprietary knowledge (Hayek, 1945). This is an inherent advantage of a buy strategy over a make strategy. A buy strategy also allows firms to quickly access suppliers’ capabilities that are not currently maintained within the firm in the new innovation context. Embarking in varied experimentation with suppliers might stimulate firms to cultivate refined information filters and communication channels (Henderson and Clark, 1990) to better respond to radical technological changes (Arthur and Rousseau, 1996; Baba et al., 2004). Hence, choosing a buy strategy yields
opportunities for firms to more effectively reduce hierarchical hazards (Brown and Eisenhardt, 1997; Spencer, 2003). Thus, given the relative advantage of a buy over a make strategy in dealing with hierarchical hazards, this group of researchers argues that firms with a buy strategy are likely to outperform firms with a make strategy in the face of radical technological changes.

**Hypotheses**

Given the criticality regarding how to efficiently deal with both exchange and hierarchical hazards arising from radical technological changes, the arguments of both groups of researchers in the literature sound appealing. As mentioned in the Introduction, and different from the extant literature's main focus on deciding upon which sourcing strategy is better in the face of a radical technological change, this study's main interest is in investigating the research question:

**RQ1.** How can firms improve the performance of their chosen sourcing strategy when dealing with radical technological change?

This study suggests two distinctive moderating factors improving performance of a make strategy and a buy strategy—the in-house retention of outsourced components knowledge and prior exploratory technological experience.

Regarding the in-house retention of outsourced component knowledge (i.e. retaining knowledge concerning component C2 in-house, some scholars have already suggested that firms should retain knowledge in the realm of outsourced components (Brusoni et al., 2001; Park and Ro, 2011). That is because after outsourcing components, firms tend to lose knowledge and capability regarding outsourced components. Firms, therefore, suffer during component integration, which is required to successfully address future (radical) innovations. However, the literature does not provide much of an explanation on the role of the in-house retention of outsourced component knowledge in reducing (exchange) hazards arising from radical technological changes.

Regarding prior exploratory technological experience, some firms may or may not possess previous experience in dealing with radical innovations when a new radical innovation comes to market. In the bicycle gear shifting case above, prior exploratory technological experience refers to whether a derailleur firm faced a similar technological innovation to index shifting technology. For example, some firms held pre-index shifting innovation experiences. Macher and Boerner (2012) developed arguments on the impact of prior exploratory technological experience on firm performance. Given that the fundamental mechanism of the make strategy and buy strategy is different (Nickerson and Zenger, 2004; Williamson, 1985), the role of prior exploratory technological experience in reducing exchange hazards by the choice of a buy strategy, and reducing hierarchical hazards by the choice of a make strategy, are likely to be different. However, the current literature simply argues that prior experience with radical innovations will positively affect the performance of both firms pursuing a make strategy and firms pursuing a buy strategy. They ignore its distinctive role in reducing hazards and improving on the performance of firms pursuing a make strategy from firms pursuing a buy strategy.

This study addresses these theoretical limitations in this study.

**In-house retention of component knowledge and exchange hazards in buy strategy.** Given that it is critical for firms pursuing a buy strategy to efficiently address potential exchange hazards for performance advantage (Grant, 1996; Kogut and Zander, 1992; Monteverde, 1995; Nickerson and Zenger, 2004), this study’s argument is that firms that keep outsourced component knowledge in-house (i.e. retaining knowledge concerning component C2) are more likely to efficiently deal with exchange hazards than firms that do not retain
such knowledge. Firms maintaining greater degrees of component knowledge in-house are better suited to identify and evaluate new knowledge originating beyond their boundaries than those that possess little or no component knowledge. Since firms that retain more component knowledge possess a deeper understanding of how to absorb, leverage or create new knowledge, they are more proficient at selecting capable project partners and shunning low-quality partners (Akerlof, 1970; Brusoni et al., 2001).

In addition, by retaining more component knowledge in-house, firms can more properly evaluate a supplier’s capabilities, judge its aptitude to perform, and furnish feedback through technological transactions (Akerlof, 1970). The retention of relevant knowledge concerning outsourced projects has helped outsourcing firms enact guidelines that their suppliers should follow (Tiwana and Keil, 2007), allowing for more effectual monitoring of outsourced activities (Mayer and Salomon, 2006; Powell et al., 2005). The in-house retention of outsourced component knowledge will likely help the firm follow the progress of a supplier’s activities (Park and Ro, 2011). And, it also helps the firm hinder any attempts of suppliers to shirk responsibility (i.e. engage in opportunistic behaviors). In sum, the in-house retention of outsourced component knowledge allows firms to efficiently deal with exchange hazards.

In contrast, a firm that possesses little or no component knowledge in-house would likely have difficulty monitoring suppliers’ activities and preventing any opportunistic behaviors since it would be its suppliers that would likely possess the relevant design and manufacturing knowledge.

Some studies have suggested that firms whose current exchange (or hierarchical) hazards innovations are not properly aligned with the appropriate sourcing strategy are likely to suffer performance consequences. As an example, Leiblein et al. (2002) showed that a firm’s technological performance is dependent on the alignment between the sourcing decision of a firm and the degree of exchange hazards. Similarly, in the US semiconductor market, Macher (2006) discovered that organizations that governed transactions appropriately in the face of a new innovation exhibited higher technological performance (i.e. shorter lead times) than those that did not govern transactions appropriately to the degree of exchange and hierarchical hazards. If it is true that the appropriate sourcing strategy decision to the degree of exchange or hierarchical hazards provides technological performance benefits, then those firms that keep more component knowledge in-house in the face of exchange hazards are more likely to show better performance. The line of reasoning above leads to the first hypothesis:

**H1.** Among firms pursuing a buy strategy, the more component knowledge a firm keeps in-house, the more likely the firm will show better technological performance in the face of radical technological change.

**Prior radical innovation experience and hierarchical hazards in make strategy.** Since it is critical for firms pursuing a make strategy to efficiently address potential hierarchical hazards for performance advantage (Abecassis-Moedas and Benghozi, 2012; Balakrishnan and Wernerfelt, 1986; Harrigan, 1984; Powell et al., 1996; Spencer, 2003), this study argues that prior exploratory technological experience (i.e. whether a firm has prior experience with radical innovations when a new radical innovation this the market) will likely allow firms pursuing a make strategy to reduce the possibility of being exposed to hierarchical hazards. Through frequent prior radical innovation experience endeavors, firms can develop capabilities entailing search for increasing variations, risk taking and experimentation to produce innovative or disruptive competencies, far different from the simple refinement and expansion of extant resources. Since firms which have more prior radical innovation experience are more cognizant of why they should rapidly adopt
new and novel technologies in high velocity markets, they can continuously improve existing processes and voluntarily pursue new possibilities in the face of radical technology shifts (Raisch and Birkinshaw, 2008). The firm with greater technological experience is constantly willing to survey existing customers’ demands and satisfy them creatively (Lubatkin et al., 2006). These experiences, thus, help firms pursuing a make strategy identify and acquire new external knowledge beyond their hierarchy and boundaries. In the process of understanding this new external knowledge, firms may try to efficiently convey technical requirements to their various product lines to ensure that specifications for the dissemination of new technology are followed. Through the process of trial and error in integrating newly acquired knowledge with existing knowledge, the firm is likely to realize that its current capabilities are not suited for the new technology. Overhauling organizational routines can lead firms to develop new firm-specific information channels and communication routines. In so doing, firms can reduce the possibility of becoming stuck in their obsolete firm-specific information channels and routines, enabling firms to avoid hierarchical hazards.

In contrast, firms lacking prior exploratory technological experience (prior experience with radical innovations) may focus excessively on exploitation activities and may overlook opportunities to overcome hierarchical hazards in dealing with a new technology (Koberga et al., 2003). This reasoning leads to this study’s second hypothesis:

**H2.** Among firms pursuing a make strategy, the more prior exploratory technological experience a firm possesses, the more likely the firm will show better technological performance in the face of radical technological change.

**Make strategy with prior radical experience vs buy strategy with prior exploratory technological experience.** In H2, this study develops arguments that prior exploratory technological experience will likely reduce hierarchical hazards in pursuing a make strategy. It should be noted that firms pursuing a buy strategy can also possess prior exploratory technological experiences (prior experience with radical innovations). However, firms pursuing a buy strategy with prior exploratory technological experience are not likely to enjoy as many performance advantages as firms pursuing a make strategy with the same.

As explained in H1, in pursuing a buy strategy in the face of radical technological change, one key issue is how firms efficiently deal with exchange hazards arising from the buy strategy choice. Prior exploratory technological experience is not likely to be that helpful in reducing exchange hazards in a buy strategy context. Dealing with radical technological change is not a one-time deal. It requires firms to continuously engage in component innovations to realize premium initial performance of the new radical technological innovation (Adner and Kapoor, 2010). Given the high component interdependence innate to radical technological changes, the addition of new knowledge may necessitate the addition, removal or reconfiguration of supplier components. Such high connectivity can make the writing and enforcing of contractual arrangements very difficult (Pisano, 1990). This renegotiation cycle can expose firms to supplier opportunism and lead to excessive exchange hazards. Given that inherently incomplete market contracts can lead to a cycle of contractual concessions and compromises as disagreements arise (Pisano, 1990) and expose transaction partners to opportunistic behaviors (Williamson, 1985), prior exploratory technological experience may reduce suppliers’ opportunistic behaviors to some extent (Mayer and Salomon, 2006) but cannot guarantee the crafting of contracts that account for all potential contingencies.

In contrast, as argued in H2, prior exploratory technological experience helps firms pursuing a make strategy reduce hierarchical hazards. Thus, a buy strategy with prior
exploratory technological experience is unlikely to provide firms with greater performance advantages than a make strategy with prior exploratory technological experience. As a result, this study presents its final hypothesis:

H3. When pursuing a make strategy, the more prior exploratory technological experience firms possess, the more likely they will show better technological performance than firms pursuing a buy strategy in the face of a radical change of technology.

Method

Sample and data collection
Individual derailleur/freewheel sets for each new drive train model were chosen as the unit of analysis. This allowed us to examine derailleur firms’ sourcing decisions regarding freewheels for each new drive train model. Overall, the data set included comprehensive information for 15 firms and 386 observations between 1980 and 1992. During this time, a primary source of information within the bicycle industry involved associated trade publications. Both bicycling enthusiasts and technicians used these publications for technical knowledge and instruction. Bicycling was one of the industry’s leading trade magazines. The samples for this study stemmed from Bicycling’s Super Spec Database (SSD). The periodical described in detail not only bicycle and part prices, but also contained information regarding performance, shifting mechanisms, component compatibility issues, component assembly instructions, etc. They provided a large and detailed database, the SSD, which specified model titles, component names and different freewheel manufacturers. In this database, 15 major firms were found, accounting for approximately 95 percent of all firms in the market. For data source reliability, this study also acquired another database, called the Buyer’s Guide (BG) database, provided by another leading trade magazine, Bicycle Annual. With Bicycle Annual’s BG database, a similar size of sample firms, drive train sets, and observations were obtained. The statistical results from both Bicycling’s and Bicycle Annual’s databases proved similar as well. Other archival sources such as the Proceedings of the International Cycling History Conference, the book Dancing Chain, and Sutherland’s Handbook for Bicycle Mechanics (6th ed.) also provided understanding of market and technological changes. Through the process of data collection and analysis, this study collected a rather extensive data set.

Measures
Dependent variable. This study used shifting timing as its dependent variable as a measure of technological performance. Shifting timing relates to how efficiently the bicycle gear shifting system changes gears (chains) across freewheels without friction. Shifting timing was evaluated by either early or late shifting performance. Early-shifting derailleurs switched gears within a quarter-turn of the freewheel while late-shifting derailleurs often required a half-turn of the freewheel or more. Early-shifting systems produced less sliding friction between the chain and the freewheel. A late-shifting rear derailleur required greater lever force and would often jump a gear or miss a shift. Essentially, the earlier shifting occurred, the better the performance.

Because bicycle trade periodicals were reliable and widespread sources of information, firms carefully scrutinized published test results concerning shifting performance. Sometimes derailleur firms and trade periodical editors would argue over test results that did not highlight a company favorably. On account of this scrutiny given to its performance tests, Bicycling endeavored to be careful and impartial. To provide objective performance tests, Bicycling would run each derailleur through a series of 16 different shifts. After each shift, the tester would manipulate the shift lever until the jockey pulley of the derailleur was
aligned underneath the freewheel cog. With the usage of specialized test equipment, *Bicycling* accurately recorded the start and finish point of each gear shift. For each drive train model within a specific year, through discussion with technical editors and industry analysts, *Bicycling* recorded shifting timing on an evaluation scale ranging from 1–10; 10 served as the highest rating.

Finally, the performance ratings for each gear shifting set were later normalized for each corresponding market segment. The bicycle gear shifting market was normally split into three price segments—low, medium and high (explained in further detail in the Control Variables section). The performance of a particular gear shifting set was compared with the average performance of the market segment within which that particular set was sold.

**Independent variables**

*In-house retention of outsourced component knowledge.* This variable was assessed by the number of patents related with the freewheel set (Hoetker, 2005). Over a dozen industry experts[1] verified that knowledge of the freewheel component incorporated knowledge encompassing a set of three important sub-components: the freewheel cog teeth, the gap between freewheel cogs and the design of the inner hub connected to the freewheel. These experts also specified the patent subclasses 474/78-297 and 475/269-330 as the main subclasses for all derailleur- and freewheel-specialized firms. This variable was counted as the number of freewheel sets and freewheel-related patent applications filed by a firm over the three years prior to the firm’s commercialization of a gear shifting system.

This variable was grounded in data acquired from the United States Patent & Trademark Office. The Patent Cooperation Treaty (PCT) is a transnational patent law treaty establishing a consistent procedure for filing patent applications to guard inventions in different contracting regions. In spite of the PCT’s existence, a PCT application does not by itself assure the granting of a patent since, in essence, global patents do not exist. Even if a firm acquires a patent in one country, the firm still needs to file for patent protection in other countries. Therefore, this investigation concentrated on patents filed in the US bicycle market.

*Prior exploratory technological experience.* An analysis of the bicycle industry literature and consultation with industry experts highlighted the important role of prior exploratory technological experience in dealing with index shifting technology. Although 1985 is officially considered the year that index shifting was introduced to the market by Shimano, with the help of industry experts and archival analysis, it was learned that prior to 1985, several firms had already attempted to introduce earlier versions of index shifting systems. These early attempts at index shifting were dubbed pre-index shifting systems. They were not marketed heavily initially and most bicycle enthusiasts were unwilling to pay a premium for these products since little attention was given to them.

Technologically, the pre-index shifting drive trains were also quite different from their more conventional counterparts. Designs for each derailleur and freewheel, and the linkage between them, were notably different and their shifting mechanisms were incompatible with traditional bicycles. Not surprisingly, firms that experimented with pre-index shifting systems may have possessed different technological capabilities that enabled them to deal with index shifting technology when it hit the market in 1985. This study found which firms introduced pre-index shifting systems prior to 1985 and checked the compatibility of drive train models between pre-index and traditional shifting systems.

Regarding component incompatibility, *Sutherland’s Handbook for Bicycle Mechanics* (6th ed.) was consulted. This handbook contained over 700 pages with very detailed figures and explanations on various bicycle components and their assembly. Often nicknamed the *Bible* for
bicycle mechanics, the handbook contained details concerning components and their compatibility for all bicycle models from 1960 to 2005. Also, the history for pre-index shifting systems was double-checked with formal/current chief engineers, project (or technical) managers, former or current CEOs and industry experts. With this taxonomy and history, this study used the total number of prior experiences related with pre-index shifting systems for Prior Exploratory Technological Experience.

**Control variables.** Regarding the variable Make-Buy Sourcing Decision, *Bicycling*’s SSD contained information concerning firms’ decisions on make-buy strategies concerning the freewheel for each drive train set model. This study classified the firm’s decision as “Make” if a firm produced the freewheel in-house and as “Buy” if a firm completely outsourced the freewheel to a partner. Regarding radical technological change, in this study, radical technological change indicated technological punctuations caused by revolutionary breakthroughs. The variable Radical Technological Change is coded as “1” if a firm adopted included index shifting technology in their bicycles, and “0” if it did not.

This study also considered firm’s or supplier’s exploitive technological experiences (Prior Exploitive Technological Experiences) (Pisano, 1990; Williamson, 1985). With index shifting, even a minor change in a critical component could significantly affect shifting performance. Thus, depending on each drive train set, a specific freewheel was required. Even if made by the same firm, different drive train lines often required different freewheel types. Due to intricacies of the freewheel design, satisfying the totality of demanded freewheel varieties was a daunting task. The more technologically advanced freewheel suppliers could provide several different freewheel varieties. Prior Exploitive Technological Experiences was, thus, measured by the number of freewheel varieties (types) provided by each supplier.

Derailleur Age was determined as the number of years that a firm spent producing the derailleur. A firm could gain more proficiency at making derailleur components over time since it becomes acquainted with the design and manufacturing processes that produce them in addition to the sourcing arrangements involved in purchasing freewheel components from suppliers. First Index Shifting System indicates the time elapsed between the release year of the derailleur/freewheel model and the year a firm first adopts index shifting technology. The earlier a firm adopts index shifting technology (implying a longer duration), the better its capabilities in dealing with derailleur and freewheel designs.

In addition, the complexity of the derailleur (Derailleur Complexity) could directly impact shifting performance. The most complex derailleurs included three crucial features—a two spring-loaded pivot, a slant parallelogram, and a Shimano-style cage geometry (Berto, 2005)—that were integrated over time as derailleur designs. Thus, the complexity of the derailleur was determined by whether it included one, two, or all three of these features. The derailleur complexity was rated as “0” if it included none of the three characteristics, “1” if it included only one of the three, “2” if it included two of the three and “3” if it included all three features. Sourcing Duration was measured as the duration of time (in years) that a firm pursued its current make-buy sourcing orientation. Market share was used as a proxy for Firm Size and was calculated in *Bicycling*’s SSD, and Firm Age was defined as the length of time (in years) that a firm produced derailleur components. For the 15 sample firms in this study, the variable Firm Dummies was used to capture any unmeasured heterogeneity present across panels.

**Instrumental variables.** To carry out the analysis, a two-stage switching regression model (Hamilton and Nickerson, 2003) based on Heckman’s (1979) method was used. This type of regression model without instrumental variables can result in unstable and unreliable parameter estimates[2] so the instrumental variables should be captured in the first-stage
estimation and not the second stage. This study included two instrumental variables. Number of Freewheel Suppliers accounted for the effect that fluctuations in bargaining power due to the population of available suppliers would have on firms’ make-buy preferences (Pisano, 1990; Williamson, 1985). This measure was assessed by tallying the number of freewheel firms that produced freewheels. In 1985, the year index shifting technology came to market, the demand for bicycles with index shifting dramatically increased (Fixson and Park, 2008). The sales volatility for bicycle models may have had a direct impact on whether firms utilized a make or buy strategy (Dess and Beard, 1984). As with Levy (1985), the log of firm bicycle sales was regressed on a time trend. The variance of the error term was then used to determine Market Demand Fluctuation.

Analysis
Empirically testing the relationship between the make-buy decision on technological performance is not a simple problem due to endogeneity (self-selection or invisible factor) concerns (Hamilton and Nickerson, 2003). Firms seldom approach the make-buy decision as mutually exclusive (Baldwin, 2007). The decision is often biased in one preferential direction due to the inclination of a firm to select a particular line of action. As a result, normative implications drawn from the regression which do not allow for endogeneity may be incorrect (Leiblein et al., 2002). Applying interaction terms can also lead to biased estimations (Mayer and Nickerson, 2005) due to their correlation with the original terms (Greene, 2003). This study, thus, used a two-stage switching regression model (Heckman, 1979) that corrected for such treatment effects. Endogeneity problems also stem from technological changes. When technology deviates radically from a stable paradigm, firms often tax the capabilities of their design processes, increasing supplier selection costs and yielding greater influence to unobserved factors. Although difficult to test, this logic casts serious skepticism on the results that combine low and high degrees of technological change into a single estimator. This study, therefore, estimates high and low technological change in separate regressions.

The first stage in Heckman’s (1979) regression model is the selection (sourcing decision) model dealing with firms’ make-buy sourcing decisions in the face of radical technological change. The goal in this model is to obtain the inverse Mills ratio via a probit model which is then incorporated into the second stage. The standard error for robustness and within-firm clustering was modified by using the clustering option in STATA. In the second stage, the technological performance model is estimated, which is of primary interest in this study. The two instrumental variables No. of Freewheel Suppliers and Market Demand Uncertainty were omitted at this stage without their omission, the estimate of predicted sourcing strategy would be determined solely by the nonlinearity of the sourcing decision model. To account for firm-level effects, this study again allowed for standard error cluster estimates at the firm level.

To obtain the final performance model, numerous steps were undertaken at each stage. A standard OLS regression was first run. To account for firm-level effects, cluster estimates of standard error at the firm level were presented. Large differences between the conventional OLS standard errors and the robust (cluster) corrected values were also found. The large differences in magnitude among the standard deviations suggested the presence of firm-level latent effects. Next, a generalized Hausman (1978) specification test for fixed vs random effects was run, and the fixed-effect model prevailed. The firm-specific residual in this study was likely to stay constant for multiple observations from the same firm but differ between firms (Bowen and Wiersema, 1999; Greene, 2003). To more properly embody firm level effects, firm size and firm age were added as well as firm dummies, which controlled for several constant firm level factors. Finally, regarding autocorrelation which often occurs in panel data analysis, the Wooldridge (2002) test was used to check for
the existence of autocorrelation of the technological performance model by using “xtserial” in STATA. The test result could not reject the null hypothesis of no first-order autocorrelation[3]. To be free from AR(1) autocorrelation, “xtregar” in STATA was used.

Results
The summary statistics and correlation coefficients for the variables in this study are displayed in Table I.

The first-stage selection model in Model 1 captures firms’ decisions on the make-buy strategies in the face of radical technological change. The coefficient for Radical Technological Change in Model 1 of Table II proved to not be statistically significant (−0.235, not significant). This indicates that the sample firms in this study did not exhibit a strong tendency to pursue one particular sourcing strategy over another when faced with index shifting technology.

Models 2 to 5 relate to technological performance. Regarding control variables, Radical Technological Change coefficients in Models 2 and 3 are relevant to the interaction effect between Radical Technological Change and the make-buy sourcing decision on technological performance. Both Radical Technological Change coefficients of the make and buy strategies in Models 2 and 3 are significant (+0.197*** for Buy in Model 2, and +1.659*** for Make in Model 3 of Table II). The results suggest that regardless of whether a firm chose a make or buy strategy, adopting index shifting technology, i.e., radical technological change, seemed to be critical for performance improvement. Also, firms that were larger (Firm Size) were likely to show better performance. Also, the inverse Mills ratio in Model 5 is significant (−0.382* in Model 5), indicating that invisible factors that potentially affect the performance of firms pursuing a make strategy in dealing with radical technological change exist. All the other inverse Mills ratios in Models 2, 3 and 4 remain non-significant, indicating that invisible factors may not be that critical for performance improvement.

Regarding H1 (the impact of the in-house retention of outsourced component knowledge on technological performance when pursuing a buy strategy), In-house Retention of Outsourced Component Knowledge in Model 2 was significant (+1.250***). And, among bicycles that adopted index shifting technology, In-house Retention of Outsourced Component Knowledge in Model 4 was significant (+1.786***). These results suggest that as technology radically shifted due to the advent of index shifting technology, firms that kept more outsourced component knowledge in-house when pursuing a buy strategy were more likely to improve shifting timing. These findings, therefore, strongly support H1.

Regarding H2 (the impact of Prior Exploratory Technological Experience on technological performance in pursuing a make strategy), Prior Exploratory Technological Experience in Model 3 was significant (+2.461***). In addition, among bicycles that adopted index shifting technology, Prior Exploratory Technological Experience in Model 5 was significant (+4.534***). These results suggest that in the face of a radical technological shift, the more prior exploratory technological experience firms possessed in pursuing a make strategy, the more likely they were to improve shifting timing. These findings seem to strongly support H2.

Regarding H3 (the performance comparison between a make strategy and a buy strategy with prior exploratory technological experience), while the coefficient of Technological Change for a buy strategy in Model 2 was +0.103 (not significant), the coefficient for a make strategy in Model 3 was +2.461***. In addition, among bicycles adopting index shifting technology, while the coefficient of Technological Change for a buy strategy in Model 4 was −0.045 (not significant), the coefficient for a make strategy in Model 5 was +4.534***. These results suggest that prior exploratory technological experience was more likely to improve performance for firms choosing a make strategy than for firms choosing a buy strategy, strongly supporting H3.
<table>
<thead>
<tr>
<th>1. Technological Performance</th>
<th>1.000</th>
</tr>
</thead>
<tbody>
<tr>
<td>2. Outsourced Component Knowledge</td>
<td>+0.169** 1.000</td>
</tr>
<tr>
<td>3. Prior Exploratory Technological Experience</td>
<td>+0.407** +0.340** 1.000</td>
</tr>
<tr>
<td>4. Radical Technological Change</td>
<td>+0.101 +0.233** +0.021</td>
</tr>
<tr>
<td>5. Sourcing Duration</td>
<td>+0.244** -0.629** +0.542** +0.015 1.000</td>
</tr>
<tr>
<td>6. Derailleur Age</td>
<td>-0.055 -0.016 -0.013 -0.089 -0.061 1.000</td>
</tr>
<tr>
<td>7. Derailleur Complexity</td>
<td>-0.060 -0.033 -0.014 -0.052 -0.017 +0.064 1.000</td>
</tr>
<tr>
<td>8. Firm Size</td>
<td>+0.049 -0.119* +0.037 +0.015 +0.149** -0.022 +0.035 -0.007 1.000</td>
</tr>
<tr>
<td>9. Firm Age</td>
<td>+0.012 -0.038 -0.014 -0.063 +0.117 -0.029 -0.004 +0.056 -0.007 1.000</td>
</tr>
<tr>
<td>10. Product Differentiation</td>
<td>+0.048 -0.006 +0.061 +0.021 +0.028 -0.000 +0.015 +0.015 -0.056 -0.023 1.000</td>
</tr>
<tr>
<td>11. Prior Exploitive Technological Experiences</td>
<td>+0.121* +0.059 +0.009 +0.009 +0.025 -0.005 -0.003 +0.043 -0.002 -0.010 -0.125* 1.000</td>
</tr>
<tr>
<td>12. First Index Shifting System</td>
<td>-0.056 -0.186** -0.094 +0.028 +0.229** -0.011 -0.017 -0.118* +0.013 -0.009 +0.154** -0.011 1.000</td>
</tr>
<tr>
<td>13. No. of Freewheel Suppliers</td>
<td>-0.056 +0.304** -0.288** -0.171** -0.411** +0.013 -0.011 +0.048 -0.056 -0.022 -0.030 -0.031 -0.150** 1.000</td>
</tr>
<tr>
<td>14. Market Demand Fluctuation</td>
<td>-0.056 -0.349** -0.302** +0.102* +0.553** -0.033 -0.024 -0.086 +0.134** +0.121 +0.020 -0.065 +0.167** -0.333** 1.000</td>
</tr>
<tr>
<td>Mean</td>
<td>0.689 0.935 0.394 0.569 0.363 0.261 0.223 1.285 0.090 14.598 0.889 6.835 3.415 34.560 0.027</td>
</tr>
<tr>
<td>SD</td>
<td>0.208 1.135 0.396 0.486 0.481 1.344 1.043 2.854 0.165 16.284 0.814 4.834 2.494 8.162 0.013</td>
</tr>
<tr>
<td>Max.</td>
<td>10 3 1 1 1 70 3 15 0.63 70 2 18 9 42 0.063</td>
</tr>
<tr>
<td>Min.</td>
<td>1 0 0 0 0 0 1 0 0.01 1 0 1 0 16 0.002</td>
</tr>
</tbody>
</table>

Notes: *0.05; **0.01
Table II. Estimating results (technological performance)

<table>
<thead>
<tr>
<th></th>
<th>First stage (Selection)</th>
<th>Sample: all</th>
<th>Sample: bicycles adopting index shifting technology</th>
<th>Dependent: CK Relationship between CK and PETE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2 (H1 and H3)</td>
<td>Model 3 (H2 and H3)</td>
<td>Model 4 (H1 and H3)</td>
</tr>
<tr>
<td>Radical Technological Change (TQ)</td>
<td>-0.235 (0.168)</td>
<td>+1.197*** (0.255)</td>
<td>+1.650*** (0.433)</td>
<td>-</td>
</tr>
<tr>
<td>In-house Retention of Outsourced Component Knowledge (CK)</td>
<td>-</td>
<td>+1.250*** (0.113)</td>
<td>-</td>
<td>+1.786*** (0.140)</td>
</tr>
<tr>
<td>Prior Exploratory Technological Experience (PETE)</td>
<td>-0.005 (0.006)</td>
<td>+0.001 (0.008)</td>
<td>-0.004 (0.012)</td>
<td>-0.003 (0.013)</td>
</tr>
<tr>
<td>Derailleur Age</td>
<td>-0.020 (0.071)</td>
<td>-0.115 (0.098)</td>
<td>-0.195 (0.154)</td>
<td>+0.273** (0.135)</td>
</tr>
<tr>
<td>Derailleur Complexity</td>
<td>+0.085*** (0.030)</td>
<td>-0.015 (0.053)</td>
<td>-0.015 (0.079)</td>
<td>+0.028 (0.069)</td>
</tr>
<tr>
<td>First Index Shifting System</td>
<td>+0.057 (0.104)</td>
<td>+0.014 (0.143)</td>
<td>+0.148 (0.203)</td>
<td>+0.151 (0.201)</td>
</tr>
<tr>
<td>Product Differentiation</td>
<td>-0.105 (0.034)</td>
<td>+0.022 (0.048)</td>
<td>+0.002 (0.053)</td>
<td>-0.034 (0.067)</td>
</tr>
<tr>
<td>Sourcing Duration</td>
<td>+1.749** (0.892)</td>
<td>+1.210 (1.310)</td>
<td>+0.218 (1.312)</td>
<td>+3.856** (1.794)</td>
</tr>
<tr>
<td>Firm Size</td>
<td>+0.010* (0.005)</td>
<td>-0.002 (0.007)</td>
<td>-0.013 (0.009)</td>
<td>-0.003 (0.010)</td>
</tr>
<tr>
<td>Firm Age</td>
<td>+0.031 (0.017)</td>
<td>+0.033 (0.030)</td>
<td>+0.065* (0.035)</td>
<td>+0.023 (0.044)</td>
</tr>
<tr>
<td>Prior Exploitive Technological Experiences</td>
<td>-0.054*** (0.011)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>No. of Freewheel Suppliers</td>
<td>+6.187*** (1.796)</td>
<td>+0.099 (0.434)</td>
<td>-</td>
<td>-0.440 (0.647)</td>
</tr>
<tr>
<td>Market Demand Fluctuation</td>
<td>-0.200 (0.293)</td>
<td>-</td>
<td>+0.420 (0.647)</td>
<td>-</td>
</tr>
<tr>
<td>Firm Dummy</td>
<td>-0.116 (0.645)</td>
<td>+4.221*** (0.655)</td>
<td>+5.192*** (0.843)</td>
<td>+2.693*** (0.976)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.106 (1.451)</td>
<td>+5.989*** (0.515)</td>
<td>+5.739*** (0.713)</td>
<td>+8.161*** (0.513)</td>
</tr>
<tr>
<td>n</td>
<td>386</td>
<td>246</td>
<td>140</td>
<td>151</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-157.25</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Overall $R^2$</td>
<td>0.374</td>
<td>0.407</td>
<td>0.407</td>
<td>0.437</td>
</tr>
<tr>
<td>$F$ Statistic</td>
<td>120.60***</td>
<td>5.99***</td>
<td>5.73***</td>
<td>8.161***</td>
</tr>
</tbody>
</table>

Notes: Robust (Cluster) standard error in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01
Discussion and conclusion

Theoretical contribution
This study’s main contribution is to advance the understanding of the technology management literature regarding how to efficiently deal with hazards arising from the make-buy strategy choice in the face of radical technological change. As explained in H1–H3, the make-buy choice will cause firms to face different distinctive hazards. This study suggested two moderating factors—the in-house retention of outsourced component knowledge and the prior exploratory technological experience—for reducing exchange hazards and hierarchical hazards.

It is believed that this study is the first to explicitly investigate the role of the in-house retention of outsourced component knowledge and prior exploratory technological experience in reducing distinctive hazards arising from the make-buy choice in the face of radical technological change. The extant literature tends to focus on which of the two sourcing strategies (i.e. make or buy) provides greater performance advantages in the face of radical technological change (Abecassis-Moedas and Benghozi, 2012; Balakrishnan and Wernerfelt, 1986; Grant, 1996; Harrigan, 1984; Monteverde, 1995; Nickerson and Zenger, 2004; Powell et al., 1996; Spencer, 2003; Wolter and Veloso, 2008). Their arguments imply that if a firm realizes poor performance from employing one type of sourcing strategy (for instance, the make strategy), then the firm should switch to the other strategy (the buy strategy) to realize performance benefits.

However, a more critical problem is that even if a firm knows which sourcing strategy is preferred over the other in a given technological context, switching to a new sourcing choice is a non-trivial endeavor due to firms’ current capabilities and the uncertainty around the new sourcing choice (Haleblian et al., 2006; Zollo and Singh, 2004). Embarking on a different approach from the extant literature, this study provides theoretical implications with regards to what firms should do in order to improve the performance of their current sourcing strategy without having to switch to the alternative strategy by suggesting two distinctive moderating factors—the in-house retention of outsourced component knowledge and prior exploratory technological experience. This study discovered that in the US mountain bicycle gear shifting market, the in-house retention of outsourced component knowledge tended to improve the performance of a buy strategy. And, prior exploratory technological experience (i.e. prior experience in dealing with radical innovations) tended to improve the performance of a make strategy. In sum, the in-house retention of outsourced component knowledge and prior exploratory technological experience are distinctive moderating factors improving the performance of a buy strategy and a make strategy, respectively. Not much literature addresses these moderating factors. So this study fills in the limitation of the extant literature, making the findings of this study very valuable.

A few scholarly works have looked into the positive role of outsourced component knowledge in the US bicycle market. Ulrich and Ellison (Ulrich and Ellison, 2005) studied the US mountain bicycle market and determined that designing outsourced components in-house is a strategically important matter when pursuing a buy strategy. Park and Ro (2011) also discovered that within the US road and mountain bicycle markets, firms retaining outsourced component knowledge in-house while pursuing an outsourcing strategy exhibited significant improvement in technological performance. However, these recent works do not explicitly develop arguments regarding the relationships between performance, in-house component knowledge, and prior exploratory technological experiences. Also, these studies do not investigate how the retention of component knowledge reduces exchange hazards and how prior exploratory technological experiences reduces (exchange and hierarchical) hazards for firms pursuing a make strategy and a buy strategy in distinctive ways. This study, thus, offers theoretical and practical implications for outsourcing firms concerning the management of outsourcing decisions of components in the face of an architectural innovation that is distinct from the extant literature.
Managerial implications

The findings of this study provide managers with clear implications regarding how to improve the performance of the current sourcing choice. When observing the mountain bicycle market, firms had to decide on whether to pursue a make or a buy strategy with regards to the freewheel as technology radically shifted toward index shifting. If a firm chose a buy strategy, the firm would have to deal with exchange hazards. Due to high interactions between the derailleur and freewheel components, firms could become heavily dependent on freewheel suppliers, and those suppliers could show opportunistic behavior. However, as firms retained more knowledge regarding outsourced freewheels in-house, they could better understand the freewheel components that needed to be redesigned for index shifting systems. In addition, they could better assess a freewheel supplier’s capabilities and establish methods and procedures that their suppliers should follow. The in-house retention of outsourced freewheel knowledge placed them in an advantageous position to monitor and control any opportunistic behavior displayed by suppliers, eventually reducing exchange hazards.

Similarly, if a firm chose a make strategy regarding the freewheel, the firm would have to deal with hierarchical hazards. Many firms pursuing a make strategy regarding the freewheel would remain grounded in their current routines in the face of index shifting technology, making it arduous for them to discover new technical knowledge associated with the freewheel beyond the boundaries of the firm. However, firms pursuing a make strategy are not always rigidly locked into their processes and routines. Through prior experience and experimentation with pre-index shifting systems, some firms developed various capabilities enabling them to appropriately redesign the freewheel for proper index shifting. By proactively acquiring new technical knowledge concerning the freewheel from outside their boundaries, firms pursuing a make strategy could overhaul existing information channels and communication routines and refine them into new processes to properly integrate the derailleur and freewheel and create the optimal chain gap. Prior exploratory technological experience could, thus, help firms pursuing a make strategy overcoming hierarchical hazards.

In sum, this study’s findings imply that firms pursuing a buy strategy should focus on acquiring knowledge regarding outsourced components in order to improve performance. And, firms pursuing a make strategy should engage in much radical experimentation in order to avoid being stuck in their current routines. By doing so, firms can enjoy performance advantages without having to switch to a new sourcing strategy. Considering that the cost of switching from one sourcing strategy to another one is often prohibitive (Nickerson and Silverman, 2003), the findings of this study are believed to be very valuable.

Limitations

Admittedly, this study possesses some limitations. First, this study focuses on the impact of a firm’s sourcing decision on technological performance but does not, however, focus on the make-buy decision itself. When considering radical technological shifts, a firm’s behavior regarding whey firms show heterogeneous decisions regarding the make-buy decision may be a worthy research topic to investigate. Next, this study attempted to shed light on the conditions where a particular sourcing strategy might yield performance advantages by investigating the role of component knowledge and prior exploratory technological experience in the face of radical technological change. I do not claim to provide descriptive reasons as to why some firms possess greater degrees of component knowledge than others in pursuing a buy strategy or why some firms possess greater amounts of prior exploratory technological experience than others in pursuing a make strategy. Researching specific notions as to why firms would possess such knowledge and experience in varying degrees would also be valuable.
Limitations notwithstanding, this study’s findings suggest that differences in the nature of technological change and differences in firms’ abilities to garner benefits from their knowledge of outsourced components and prior exploratory technological experience may sculpt the extent to which firms pursuing a make or buy strategy can effectively compete and coincide in a given industry. It is hoped that the results will encourage managers to broaden their consideration of sourcing decisions beyond the make-buy decision and to also be cognizant of firms’ knowledge and experience, as well as how sourcing decisions, knowledge and experience interact with changes in technology to impact performance outcomes.

Notes
1. For this variable, more than 20 individuals were interviewed in this study. Individuals who were interviewed included the likes of chief engineers, senior engineers, project (or technical) managers, and CEOs, along with industry experts, most of whom had been associated with the bicycle industry for over two decades. Interview data were gathered through semi-structured interviews. The interviews were conducted either on-site at each company or via phone or e-mail, with the typical interview ranging from 1 to 3 h.

2. When employing the two-stage switching regression model, scholars have voiced two cautions. First, variables associated with legal issues, government policy or industry and environmental changes that “all” firms (whether characterized by a buy or a make strategy) must face need to be considered (Hamilton and Nickerson, 2003). Second, these variables should affect the B-M decision but not directly affect performance. The two variables included in this study are believed to satisfy these two conditions.

3. For example, Model 2 in Table II was tested. The result could not reject the null hypothesis of no first-order autocorrelation ($F = 21.468 > 0.000$).

References


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The role of the consistency between objective and perceived environmental uncertainty in supply chain risk management

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Abstract
Purpose – The purpose of this paper is to understand how the consistency between objective and perceived environmental uncertainty might affect supply chain flexibilities that cope with supply chain risk.

Design/methodology/approach – This study adopted a case study of comparative four companies in order to obtain an in-depth knowledge of the environmental conditions under which the companies implement different types of supply chain risk management (SCRM) strategies: logistics flexibility and relationship flexibility.

Findings – The case analysis not only distinguished the different effects of objective and perceived environmental uncertainty on supply chain flexibility, but also established the propositions about the effects of the consistency between objective and perceived environmental uncertainty on logistics flexibility and relationship flexibility in SCRM.

Originality/value – In principle, supply chain flexibility aims to cope with complex and turbulent environments. Yet, empirical findings about the effects of environmental uncertainty on supply chain flexibility are inconclusive. This study addressed this question by differentiating between objective and perceived environmental uncertainty as well as between logistics and relationship supply chain flexibilities.

Keywords Supply chain risk management, Consistency, Relationship flexibility, Perceived environmental uncertainty, Logistics flexibility, Objective environmental uncertainty

Paper type Research paper

1. Introduction
Factors including rapid technological development, shorter product life cycles, more diversified customer demands and fierce market competition make today’s business world increasingly unpredictable and risky. Some firms develop effective supply chain risk management (SCRM) strategies in response to the uncertain environments, such as dynamic pricing, product assortments, multi-sourcing strategies, and vendor managed inventory.
(see Tang, 2006 for a comprehensive review), while others fail to do so. To the extent that flexibility constitutes an adaptive response to environmental uncertainty and operational risks (Sreedevi and Saranga, 2017), it is important to understand when and how such a response actually arises.

To address the question of how firms implement their flexibility strategies in response to environmental uncertainty in their SCRM, this paper distinguishes between objective and perceived environmental uncertainty, and explores the effect of (in)consistency between objective and perceived environmental uncertainty on firms’ supply chain flexibility strategies. Consistent with previous research which has classified competitive environments into three factors (i.e. objects, attributes and perceived uncertainty) (Bourgeois, 1980; Vokurka and O’Leary-Kelly, 2000), we define perceived uncertainty as management’s perceived inability/ability to accurately predict future events in their environment. According to previous studies of drivers of supply chain flexibility (Tachizawa and Thomsen, 2007; Vickery et al., 1999), perceived environmental uncertainty in the primary task environment is a critical driver of supply chain flexibility. However, the results in these empirical studies are inconclusive, some showing a positive effect (Patel et al., 2012; Swamidass and Newell, 1987) or negative effect (Han et al., 2014; Prater et al., 2001), others revealing mixed effects (Sánchez and Pérez, 2005; Vickery, et al., 1999), or even no effect (Pagell and Krause, 1999, 2004). While the centrality of environmental uncertainty as a concept dates back to pioneering contingency studies, these studies variously propose measuring environmental uncertainty either objectively (Dess and Beard, 1984; Miller and Friesen, 1983; Snyder, 1987), perceptually (Duncan, 1972; Lawrence and Lorsch, 1969; Lorenzi et al., 1981), or as a combination of both (Milliken, 1987). To address the inconsistency in the empirical findings, the present study distinguishes between objective and perceived environmental uncertainty as distinct concepts, rather than as distinct measurement modes.

Moreover, while the existing literature often treats supply chain flexibility as a unidimensional concept, this paper explores the distinctiveness of two dimensions of supply chain flexibility: intra-firm logistics flexibility and inter-firm relationship flexibility, which helps clarify how different types of supply chain flexibility arise as a response to environmental uncertainty and how they contribute to the supply chain risk mitigation. As an early example, in a sample of automotive suppliers, Sánchez and Pérez (2005) found that volume flexibility is a response to perceived demand uncertainty whilst launch flexibility is a response to perceived uncertainty about competitors. Such previous studies focus on how environmental uncertainty leads to different dimensions of intra-firm flexibility; however, the effects of objective or perceived environmental uncertainty on intra-firm logistics flexibility could be different. Logistics flexibility is unilateral and refers to the ability of the organization to respond quickly to customer needs in delivery, support and service (Zhang et al., 2002). In contrast, relationship flexibility defines a bilateral expectation of willingness in a trading relationship to adapt, change or adjust to new knowledge without resorting to a series of new contracts and renegotiations (Richey et al., 2012; Young et al., 2003).

Through a case study of four companies from two industries in China, this paper obtains an in-depth knowledge of the environment and risk conditions, under which firms within supply chains implement different types of flexibility strategies. The observations form the basis for developing propositions regarding the two types of supply chain flexibility and how they might arise as responses or adaptations to objective environmental uncertainty, perceived environmental uncertainty and the (in)consistency between these two kinds of uncertainty. Specifically, it is proposed that the consistency between objective and perceived environmental uncertainty, as an indicator of a firm’s ability of risk prediction, has a negative effect on its relationship flexibility ($P1$); as to the effect of the consistency between two types of environmental uncertainty on the logistics flexibility, a moderating effect of
objective environmental uncertainty is proposed (P2). In addition, after coding and analyzing the secondary data on risk changes in each firm, the effect of relationship/logistics flexibility in reducing supply chain risk is proposed (P3).

2. Literature review

2.1 The definition and dimensions of supply chain flexibility

Early studies of manufacturing flexibility (e.g. Gerwin, 1993; Gupta and Buzacott, 1989; Slack, 1987) and supply chain flexibility (e.g. Tachizawa and Thomsen, 2007; Zhang and Cao, 2002) define flexibility as the ability to cope with environmental uncertainty. Compared with manufacturing flexibility as the internal flexibility of a single firm, supply chain flexibility has been suggested as potentially arising at any tier of a hierarchical or cross-functional system (see review by Yu et al., 2015). Thus, supply chain flexibility is defined as a capability of coping with environmental uncertainty based on two or more functions along the supply chain, either functions internal to the firm or functions external to the firm (Vickery et al., 1999; Zhang et al., 2002). Considering the importance of inter-organizational systems and relationships, the recent definition refers to an integration of intra- and inter-organizational flexibilities and the organization’s own relationships (see review by Fayezi et al., 2017).

Previous studies have identified several dimensions of supply chain flexibility, and most add a few new dimensions to those originally related to manufacturing flexibility. The review by Yu et al. (2015) summarizes such specific dimensions as spanning flexibility (Zhang et al., 2002), organizational flexibility, information systems flexibility (Duclos et al., 2003; Golden and Powell, 1999; Stevenson and Spring, 2007), relationship flexibility and network flexibility (Gosling et al., 2010; Han et al., 2014; Liao et al., 2010; Richey et al., 2012; Wang and Wei, 2007). However, a complete definition of supply chain flexibility components should include the flexibility dimensions required by all of the participants in the supply chain in order to successfully meet customer demand (Duclos et al., 2003). According to resource-based view (Barney, 1991), two types of flexibility particularly relevant to supply chain management are logistics flexibility involving physical resources and relationship flexibility involving relational resources (Yu et al., 2013).

Specifically, logistics flexibility is unilateral and refers to the ability of the organization to respond quickly to customer needs in delivery, support and service (Zhang et al., 2002). It is resource based in that logistics flexibility involves processing material and information flow between the focal firm and its supply chain partners. For instance, to make such adjustments requires a sufficient quantity and quality of information as a resource. In contrast, relationship flexibility defines a bilateral expectation of willingness in a trading relationship to adapt, change or adjust to new knowledge without resorting to a series of new contracts and renegotiations (Richey et al., 2012; Young et al., 2003). It is norm based, in the sense that relationship flexibility is built upon the quality of the inter-firm relationship. From a supplier’s perspective, it represents an assurance that the relationship will be subject to good-faith modification if a particular practice proves detrimental in light of changed circumstances (Heide and John, 1992; Johnston et al., 2004).

2.2 Environmental uncertainty as a driver of supply chain flexibility

Empirical studies demonstrate that either perceived environmental uncertainty (Swamidass and Newell, 1987) or objective environmental uncertainty (Dreyer and Gronhaug, 2004) has a positive effect on flexibility. Thus, environmental uncertainty is identified as a key driver of supply chain flexibility (Tachizawa and Thomsen, 2007) which is an effective way to manage the supply chain risk. Objective environmental uncertainty describes the state of the organizational environment while perceived environmental uncertainty describes the state of a person (e.g. a manager) who perceives him or herself to be lacking critical
information about the environment (Milliken, 1987). As such, objective and perceived environmental uncertainty could have distinct effects on supply chain flexibility.

Compared with early studies of manufacturing and supply chain flexibility, recent studies begin to explore the moderating role played by environmental uncertainty. Some studies investigate the moderating effect of perceived environmental uncertainty on the relationship between supply chain flexibility and its performance (e.g. Merschmann and Thonemann, 2011). Other studies investigate the effect on the relationship between supply chain flexibility and its antecedents such as supply chain integration (e.g. Wong et al., 2011) and knowledge transfer (Blome et al., 2014). Only Gligor (2014) and Gligor et al. (2015) adopted objective measures of environmental uncertainty and test its moderating effect on the relationship either between market orientation and supply chain orientation or between supply chain agility and customer effectiveness and cost efficiency.

As perceived environmental uncertainty only concerns with the unpredictability aspect of the uncertainty, and objective environmental uncertainty is prone to including both predictable and unpredictable uncertainty, weak to moderate correlations have been reported between objective and perceptual measures of uncertain environments (Boyd et al., 1993; Lueg and Borisov, 2014). Based on contingency theory (Donaldson, 2001), the viability or performance potential of an enterprise is determined by the fit between organizational factors and environmental state, and such environmental state is a status in reality that is quite independent of the actor’s perceptions. However, this does not mean the actors’ perceptions of the environment are not relevant; they are likely to be most important in shaping the structure and strategy adopted by an organization (Tinker, 1976). Actually, variation in objective environmental uncertainty is more about cross-industry differences, while perceived environmental uncertainty is more about within-industry cross-firm differences. Thus, the assumption is that within the same industry, objective uncertainty is the same, but firms within each industry perceive different levels of uncertainty.

As environmental scanning is a secondary strategy activity intended to support decision making (Priem et al., 2002), external objective environmental uncertainty moderates the effect on flexibility decisions of subjective cognition of environmental uncertainty by the decision maker.

2.3 Supply chain flexibility as a resistance to risk

SCRM has gained much attention from researchers recently (Lee, 2004; Rao and Goldsby, 2009; Sodhi et al., 2012; Tang, 2006). Although there has been no consensus on a definition or scope for supply chain risk, Rao and Goldsby (2009) synthesized the diverse literature into a typology of risk sources, including environmental factors, industry factors, organizational factors, problem-specific factors, and decision maker-related factors. For instance, Svensson (2000) pointed out that the vulnerability of a supply chain increases with increasing uncertainty. More recently, Sodhi et al. (2012) summarized four key elements for managing supply chain risks: risk identification, risk assessment, risk mitigation and responsiveness to risk incidents.

In this line of literature, the majority of research has covered the risk mitigation element, i.e., “reducing the likelihood of a particular risk’s occurrence, reducing its potential impact, or both” (Sodhi et al., 2012, p. 6); and there exists a lot of research focusing on how to mitigate supply chain risks (Braunscheidel and Suresh, 2009; Christopher and Lee, 2004). For instance, Christopher and Lee (2004) suggested that an important way to mitigate supply chain risks is improving “end-to-end” visibility of the supply chain.

It is worth noting that flexibility has been shown to be an important strategy to mitigate supply chain risks (Tang and Tomlin, 2008). Using data from 126 Spanish automotive suppliers in 2003, Sánchez and Pérez (2005) showed that supply, process and demand flexibilities have positive impact on business performance by reducing supply chain risks.
Tomlin (2014) pointed out that although supply-demand imbalances are a major business risk in a vast array of industries, companies can mitigate the risk by creating cost-effective flexible networks.

2.4 Research questions
It is argued that specific aspects of a firm’s environment influence specific types of manufacturing flexibility (Vokurka and O’Leary-Kelly, 2000). Ketokivi (2006) examined about how environmental contingency factors (product complexity and demand dynamism) affect the likely manifestation of distinct patterns of manufacturing flexibility strategies in a producing organization. That study employed a carefully constructed case research method aiming broadly at theory elaboration, specifically an elaboration of contingency theory. The present study employs case research with the specific aim of generating theory, in particular, the generation of a set of theoretical propositions about the consistency between objective and perceived environmental uncertainty on logistics and relationship flexibility.

It is in this context that we pose our research questions:

RQ1. Do companies located in the same objective environment perceive the same level of uncertainty? How do they then make decisions about supply chain flexibility? Does environmental uncertainty affect different types of supply chain flexibility in the same manner?

RQ2. Does the perception of the manager on environmental uncertainty affect firm’s supply chain flexibility? Does a company’s approach to supply chain flexibility depend on whether perceived environmental uncertainty is consistent or inconsistent with objective environmental conditions?

RQ3. Will the high level of supply chain flexibility (i.e. relationship flexibility or logistics flexibility) eventually reduce the supply chain risks?

3. Method
3.1 Sampling and the measure of objective environmental uncertainty
We selected four cases in two different manufacturing industries in China. China is a rich setting for the study of many decision science issues relating to supply chain management and operations strategy (Zhao et al., 2006). Furthermore, logistics strategy research in China has been virtually ignored by scholars compared to business and operations strategy research (Zhao et al., 2007).

The two different industries were selected as they have distinctive levels of objective environmental uncertainty, showing the variance of objective environmental uncertainty which fits well our research question. Objective environmental uncertainty was measured in terms of environmental munificence and instability. The method developed by Pagell and Krause (2004) to calculate objective environmental munificence and instability was adopted. Specifically, the previous five years’ sales (the manufacturing industries) were treated as the dependent variable against time (from 2006 to 2009) as the independent variable. The basic equation is given by:

\[ y_t = b_0 + b_1 t + a_1, \]

where \( y \) = industry sales or industry operating income; \( t \) = year; \( a_1 \) = residual; \( b_0 \) = intercept; and \( b_1 \) = coefficient.

The specific measure to address munificence is the anti-log of the slope of the regression described above and the specific measure to address instability is the anti-log of the standard error for the regression slope coefficient. The results show that the first
sampling industry – environmental instrumental industry – has a higher level of objective environmental uncertainty (the level of munificence is 3.913 and the level of instability is 1.2846) than the second sampling industry – power generation industry (the level of munificence is 2.798 and the level of instability is 1.0833).

The first group of two comparable cases in the environmental instrument industry is Company A and Company B. Company A was first established in 1991 as a research institute and then began its quest for world-class analytical instrumentation products in 1993. It has now become a leading company in its industry and has more than 800 employees, of which one-third are technicians. Company A uses extensive research, design and testing for the development of UV-spectrophotometers, atomic absorption spectrophotometers, water quality analyzers and medical testing instruments. Involved in pharmaceuticals, environmental testing, merchandise inspection, university research, government research, and medical and health research, Company A has a strong marketing ability. Another firm Company B was also created in 1991 and now has become a well-known environmental protection and high-tech enterprise. Company B has more than 500 employees. Mid-level and senior technical staff account for 30 percent of the total number of employees. The equipment they develop in the field of environmental protection reflects nearly two decades of scientific research and development experience and their technical strength. They hold dozens of patents. Through continuous effort and innovation, Company B has developed and produced a range of products, including an atmospheric sampler, a dust sampler, gas analyzers, an air quality monitoring system, flue gas continuous emission monitoring systems, environmental emergency monitoring and dozens of other types of intelligent environmental monitoring equipment.

The second group of two comparable cases, namely, Company C and Company D, is in the power generation industry. Company C is a state-owned enterprise, founded in October 1995 with the approval of the State Council, pursuant to Corporate Laws and has 150,447 employees. Company C is a diversified energy enterprise with major businesses concentrating on coal production, sales, electricity and thermal generation, coal liquefaction and coal chemicals, as well as railway and port transportation. As the most competitive unified energy company in China, Company C has integrated segments of coal, railway, power and ports, and pursues coal production, transportation and sales through a multi-faceted strategy. Company D is also a stated-owned enterprise, founded in December 2002. It is one of the top 5 power generation companies in China and has 126,000 employees. Company D has made equal progress on its two major business segments of hydropower and coal-fired power, and realized stable development of new projects. In respect to the coal-fired power business, they have further implemented a strategy of “large generation units” in order to optimize the distribution and structure of its coal-fired power assets and further improve its profitability. As for the hydropower business, Company D has been actively developing or acquiring small to medium-sized hydropower plants, which boast abundant hydropower resources, while steadily developing new projects. Table I shows some comparative information about the four companies. While Company A and Company B have a high level of objective environmental uncertainty, Company C and Company D are in a rather stable environment, i.e., with a low level of objective environmental uncertainty.

3.2 Coding process
We adopted content analysis, a recognized research method in the field of operations and supply chain management (Tangpong, 2011), to code perceived environmental uncertainty as well as supply chain flexibility from the interview data. Further, since the levels of environmental uncertainty perceived by the company managers could be quite different from their objective environmental uncertainty, we also coded the consistency between a firm’s perceived environmental uncertainty and its objective environmental uncertainty as
high or low. Pre-established procedures and coding schemes were developed and used to systematically classify or categorize the sources in all communication forms (e.g. Krippendorff, 2004; Weber, 1990). There were four steps as follows:

(1) The first step is determining the recoding units.

This study used the sentence and paragraph in three overlapping sources (semi-structured interviews, documents and participant communication) to maintain data consistency and improve richness in detail. Multiple interviewees within one case were encouraged to participate as this study aimed at exploring many cross-functional issues. The interview guide (Appendix) was sent a few days before the formal interviews. The key questions were about perceptions on the changes of their business environment in the most recent five years and the flexibility strategies that they had taken to respond to the changes.

(2) The second step is determining the content categories for coding.

Five coders, including two associate professors, one assistant professor and two postgraduate students within the research team reviewed all the sources from each company. The coders well understand the design method of this research and each developed a list of key issues from which a summary report was prepared (details of which are available from the authors upon request). After reaching an agreement, they deleted the redundant contents and selected only the contents related to environmental conditions and supply chain strategies. All these paragraphs or sentences were coded as free nodes in NVivo 10.0.

(3) The third step is developing coding rules.

Five coders majoring in supply chain management formed an expert team to develop the rules for coding perceived environmental uncertainty, logistics flexibility and relationship flexibility. As shown in Figure 1, three levels of nodes were established by searching for the corresponding keywords in the nodes of the lower level: on the first level, the keywords representing “environment,” “logistics” and “relationship” are searched, and the sentences containing these keywords are kept as first-level nodes; on the second level, the keywords indicating high or low uncertainty are further searched in the nodes of “environment” on the first level and the keywords indicating high or low flexibility are searched in the nodes of “logistics” as well as “relationship” on the first level, and these are kept as second-level nodes; on the third level, the keywords indicating the varying degree of high or low conditions are searched in the nodes of “high uncertainty,” “low uncertainty,” “high flexibility,” “low flexibility” as the third-level nodes. Inter-rater agreement

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<tr>
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<th>Company A</th>
<th>Company B</th>
<th>Company C</th>
<th>Company D</th>
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<tbody>
<tr>
<td>Industry</td>
<td>Environmental instrument</td>
<td>Environmental instrument</td>
<td>Power generation</td>
<td>Power generation</td>
</tr>
<tr>
<td>Location</td>
<td>Beijing</td>
<td>Wuhan</td>
<td>Beijing</td>
<td>Beijing</td>
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<tr>
<td>Firm size</td>
<td>Medium</td>
<td>Medium</td>
<td>Large</td>
<td>Large</td>
</tr>
<tr>
<td>Firm age (years)</td>
<td>23</td>
<td>23</td>
<td>12</td>
<td>19</td>
</tr>
<tr>
<td>Interviewees</td>
<td>One senior manager in marketing; one senior manager in operations</td>
<td>Two senior managers in operations</td>
<td>President; one senior manager in marketing; and two senior manager in operations</td>
<td>President; and two senior managers in operations</td>
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<td>Complementary materials</td>
<td>Website, brochure, customer feedbacks</td>
<td>Website, brochure, customer feedbacks</td>
<td>Website, financial reports, meeting records, consulting report</td>
<td>Website, financial reports, speech draft, manager debrief</td>
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Table I. Profile of the four companies
(IRA) was computed as the number of keywords considered at least 80 percent reliable divided by the total number of keywords (Rubio et al., 2003). The keywords list was continuously adjusted until the average IRA for each construct was 100 percent.

4. Case analysis and propositions

4.1 Environmental uncertainty, logistics flexibility and relationship flexibility

As shown in Table II, we analyzed perceived environmental uncertainty from two dimensions: perceived uncertainty in demand and perceived uncertainty in competition, two important dimensions of the supply chain environment. For company A, both the level of demand uncertainty and the level of competition uncertainty perceived are the highest among the four companies. Compared with Company A, Company B perceives the external environment to be very stable and their instruments only need to conform to national standards. Similarly, the level of perceived environmental uncertainty of Company C is also low due to their analysis of the corresponding policies that maintain a stable development of the power industry. However, Company D orients more toward the market and focuses on the part of it outside the plan of the government, so they perceived a higher level of environmental uncertainty although lying in the same industry as Company C.

In Table III, based on the definition of logistics flexibility and relationship flexibility, we compared the level of logistics flexibility from the aspects of service/resource/product delivery, transportation, inventory management and order fulfillment; and the level of relationship flexibility from the aspects of relationship content, agreement and solutions. Ranking cases from high to low levels of logistics flexibility, the sequence is Company A,
Company D, Company B and Company C. The high level of Company A presents three facets: flexible service delivery, flexible inventory management and flexible order fulfillment. In contrast, the level of logistics flexibility is much lower in Company B. They do not have a variety of value-added services and have a fixed level of production output for inventory each year. They produce for planned demand and use safety stock rather than
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<th>Category</th>
<th>Company</th>
<th>Codes</th>
<th>Original quotes</th>
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<tbody>
<tr>
<td>Logistics flexibility</td>
<td>Company A</td>
<td>Flexible service</td>
<td>“Another thing is about after-sales services [and] responding time […] We have more than 500 sales people, branches and maintenance stores in each province, so no matter when you call us, we will arrive the next day.” “It took almost half a day to get the results before, but now only ten minutes.” “When reports arise that pollution exists somewhere, they can arrive quickly to begin work”</td>
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<td></td>
<td>(very flexible)</td>
<td>delivery</td>
<td>Flexible inventory management “For inventory, we also try to find the meeting point […] All the instruments are controlled together. When the demands are proposed from 30 provinces, all [inventory] are sent from Beijing.” “For new products, we have little data to forecast the market. You send the order and we produce, so there is no inventory. However, for traditional products like UV-spectrophotometers, we know the annual demand in this market, so we would have a certain amount of safety stock. When stock is below this level, we have to produce no matter whether orders exist or not”</td>
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<td>Flexible order fulfillment “For example, we bid for a big order that everything from monitoring to final [analyzing] are included. For one part, we can do it ourselves; while for the other part, we should outsource it. Like a government purchase, there are 10 kinds of instruments, among which we could only supply half of them and buy the remainder from others […] We also accept others’ outsourcing. For example, one national lab is purchasing instruments. We could supply atomic absorption spectrophotometers, but other parts such as some glassware that we do not have will be purchased from others”</td>
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<td></td>
<td>Company B</td>
<td>Rigid service</td>
<td>“After the quality guarantee period, there are a large quantity of maintenances, so who will take charge of it? If the pollution emission firms themselves, then we will only take charge of the faults of the instrument, but maintenance and calibration will be all your own business.” “We keep on selling instruments, while selling operations is another kind of business which may not hand to you […] Instrument is only instrument, and maintenance is only maintenance”</td>
</tr>
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<td></td>
<td>(rigid)</td>
<td>delivery</td>
<td>Rigid inventory management “Every year there will be a certain amount of productivity.” “[The inventory] will not be a large quantity […] The inventory of hand sampling [instrument] would be relatively large as the price is not very high”</td>
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<td></td>
<td></td>
<td></td>
<td>Company C</td>
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<tr>
<td></td>
<td>(very rigid)</td>
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<td>Rigid transportation</td>
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Table III. Comparison of supply chain flexibility among four companies

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<th>Company</th>
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<th>Original quotes</th>
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<tr>
<td></td>
<td>Rigid inventory</td>
<td>management</td>
<td>“Based on e-report of resources each month and two assessment indexes [resource purchasing and inventory] proposed at the beginning of the year, we can monitor the process of resource management.” “The inventory management among different units lacks of combination, which raises small and all-inclusive inventory. Furthermore, the total amount of inventory is simply summed rather than complemented”</td>
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<td></td>
<td>Company D</td>
<td>(flexible)</td>
<td>Flexible product delivery</td>
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<td>“First, the marketing center will determine the category and quantity of the products and then provide orders for coal mines. Second, according to the location, the amount and assortment demanded, we will plan for distribution, transportation and package exchange at the harbor, including the interface port of national railway, the quantity and direction flow of harbors etc. Finally, we deliver the products to customer on time with high quality and right quantity”</td>
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<td>Flexible transportation</td>
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<td>“Our railway branch company proposes a way of ‘combined transportation’, which breaks down the single operation of railway system. We sign transportation contracts with the corresponding railway suboffice and railway construction suboffice and the transportation fee is calculated according to ton per kilometer.” “We break 189 kilometers into 6 sections and design 1-2 loading platform in each section. After constructing one section, we operate one section and increase two pairs of trains each day, which liberates the transportation capacity”</td>
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<td></td>
<td>Relationship</td>
<td>Flexibility</td>
<td>Company A (rigid) Rigid relationship content Flexible solutions “Under unchangeable preconditions, relationship marketing is important. After all, if there are ten instruments [different brands] could achieve the standards, anyone that they [the customer] choose would be fine” “There are two kinds of solutions. One is when the customers are active, and they would provide a list as they know what they want. However, if it is a blank market, we will provide the other solution listing all the instruments which are prepared for your lab [the customer] […] We will explain to you what kind of problems this solution will deal with. If they accept, it will be fine. While if they want to negotiate, we can coordinate again”</td>
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<td>Company B (very flexible) relationship content Flexible solutions For example, some customers […] take charge of instrument operations, and only when there is something wrong with the equipment, do we come to repair it. But if you [the supplier] sell operations, you take charge of everything.” “It may be not only one instrument [to handle]. The whole district may hand to you [to operate] […] We will establish a maintenance team […] If the maintenance is profitable and the contract term is much longer, we will replace the key parts in the bad instrument with our own products.” “Our offices are everywhere, which is convenient for the sales people to visit their customers […] Each manager takes charge of one district […] After their visits, any problems would be reported to me, and I will solve them. There are neither strict regulations [of the visiting frequency] nor requirements for the number of customers”</td>
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<td>Company B Flexible agreement “[The contract] is far from being clear. There is quality guarantee period. During that period, we have to take charge of [fixing]. But the customers have not only data but also some maintenances. [which are not clear in the contract]”</td>
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(continued)
produce flexibly in response to orders. Company C is even more rigid than Company B. It presents three facets: rigid resource delivery, rigid transportation and rigid inventory management. However, in the same industry, Company D is more flexible in two respects: one is flexible product delivery and the other is flexible transportation.

Ranking cases from a high to a low level of relationship flexibility, the order is Company B, Company D, Company C and Company A. Although Company A has alternative solutions for different customers, they often keep service contracts fixed. In contrast, the level of relationship flexibility of Company B is the highest. There is no fixed frequency of maintenance but, instead, the services that they provide depend on customer demand. Similarly, Company D also shows flexible relationship content based on a supplier strategic coordination network as well as flexible solutions depending on external alliances.

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<tbody>
<tr>
<td>Rigid relationship content</td>
<td>Company C</td>
<td>(very rigid)</td>
<td>“There are two parts of our purchase: one is carrying out the yearly plan of purchase amount, quality, price and transportation, which accounts for 70% of the total purchase [...]; the other is the resource gap which is purchased independently from the spot market”</td>
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<td>Rigid agreement</td>
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<td></td>
<td>“The power stations purchase separately, which weakens bargaining power in the relationship with coal suppliers […] The power stations near the coal mines have been influenced by the monopoly of X and Y group company [coal mines] and the local distribution of coals with low quality”</td>
</tr>
<tr>
<td>Flexible relationship content</td>
<td>Company D</td>
<td>(flexible)</td>
<td>“We establish a network of coordinating external resources, which is named supplier strategic coordination network. Through this organization, we can integrate with competitive suppliers. We hold yearly meetings each year to communicate and research conferences with specific themes such as technology, marketing and so on. Besides, we have operation meeting each quarter of year including not only our internal departments but also some organizations in the coordination network to solve problems”</td>
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<tr>
<td>Flexible solutions</td>
<td></td>
<td></td>
<td>“Among our branch companies, the supplier management of X railway company is very special. We adopt the idea of transport network separation. We first implement external alliances, which focuses on separating the fixed equipment and movable equipment such as locomotives. We manage the fixed equipment, traveling direction and capacity assignment, while external alliances take charge of locomotives and trains”</td>
</tr>
</tbody>
</table>

Table III.
In contrast, the level of relationship flexibility of Company C is also very low, presenting two facets: one is rigid relationship content according to the yearly plan of purchase; and the other is rigid agreement because of weak bargaining power in the relationship with coal suppliers.

The four companies in this study also display various perceptual possibilities. Even in the same industry, different companies may perceive the external environmental uncertainty quite differently, which, in turn, leads to different levels of flexibility. Interestingly, the top managers would follow their own perceptions of the external environment and take actions based upon whether they assume the environment to be stable or uncertain. These perceptions of top managers regarding the external environment, in turn, affect the corresponding supply chain strategies. According to the analysis of four cases, we summarize their differences in Table IV.

4.2 The effects of environmental uncertainty on relationship flexibility

For relationship flexibility, the companies tried to adapt to objective information about the external environment. Company B’s manager indicates that they rely on information from the buyer’s side, for example, “Everything depends on [customer] requirements. We also want to bring in maintenance, but they may think about quality guarantee period and would like to discuss with you after the period.” Company D also collects environmental information regularly through holding “yearly meetings each year to communicate and research conferences with specific themes such as technology, marketing and so on.” However, from the coding, the effect of objective environmental uncertainty on relationship flexibility is not clear:

P1a. The effect of objective environmental uncertainty on relationship flexibility is null.

The effect of perceived environmental uncertainty on relationship flexibility may be complex. Company B, which perceives the environment to be stable, would like contracts to have very flexible terms that could be adjusted according to varying conditions. Under the same level of objective environmental uncertainty, Company A, which perceives a low level of uncertainty, often keeps service contracts fixed in terms of the time range of free maintenance, the frequency of consultancy and the contents of daily services. These observations suggest a negative effect of uncertainty on relationship flexibility. Different from Company A and Company B, Company C with a low level of perceived environmental

<table>
<thead>
<tr>
<th>Objective environmental uncertainty</th>
<th>Company A</th>
<th>Company B</th>
<th>Company C</th>
<th>Company D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived environmental uncertainty</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Frequency</td>
<td>2 (0)</td>
<td>1 (2)</td>
<td>4 (5)</td>
<td>3 (1)</td>
</tr>
<tr>
<td>%</td>
<td>50% (0)</td>
<td>33.33% (40%)</td>
<td>12.9% (22.73%)</td>
<td>20% (5.88%)</td>
</tr>
<tr>
<td>Perception consistency</td>
<td>Less consistent</td>
<td>Inconsistent</td>
<td>Very consistent</td>
<td>Inconsistent</td>
</tr>
<tr>
<td>Logistics flexibility</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Frequency</td>
<td>4 (0)</td>
<td>0 (2)</td>
<td>31 (20)</td>
<td>15 (8)</td>
</tr>
<tr>
<td>%</td>
<td>57.14% (0)</td>
<td>0 (50%)</td>
<td>54.39% (83.33%)</td>
<td>34.9% (24.24%)</td>
</tr>
<tr>
<td>Relationship flexibility</td>
<td>Low</td>
<td>Very high</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Frequency</td>
<td>1 (1)</td>
<td>3 (2)</td>
<td>18 (11)</td>
<td>8 (3)</td>
</tr>
<tr>
<td>%</td>
<td>0 (100%)</td>
<td>33.33% (0)</td>
<td>50% (61.11%)</td>
<td>32% (16.67%)</td>
</tr>
</tbody>
</table>

Notes: The frequency is for the nodes at the third level, and the percentage is the nodes at the third level to the ones at the second level. The data outside the bracket are at the high level (of uncertainty or flexibility), while the one inside is at the low level (of uncertainty or flexibility). The final level is determined by the percentage both outside and inside the bracket.

Table IV. Summaries of the comparisons
uncertainty has a low level of relationship flexibility, while Company D with a high level of perceived environmental uncertainty has a high level of relationship flexibility. These observations in the power generation industry imply a general positive effect. The opposite directions between the two groups suggest no clear direction for the effect. Alternatively, the effect might be curvilinear. Specifically, it might be inverted U-shaped: that relationship flexibility is low when the perceived environmental uncertainty is either low (as in Company C) or very high (as in Company A). Since relational flexibility is bilateral, there should be a range of modification that is tolerable for both parties. Company D has “a network of coordinating external resources” and “external alliances” which enhances the level of their tolerance, while Company A has to admit, “Under the unchangeable preconditions, relationship marketing is important.” If environmental uncertainty perceived by managers is higher than the turning point of the U shape, willingness to get a dramatic modification of relation norms may be weakened:

\[ P1b. \] The relationship between perceived uncertainty and relationship flexibility depends on the level of objective uncertainty.

There is a possibility that it is not only the level of perceived environmental uncertainty but also its consistency with objective environmental uncertainty that affects the level of logistics flexibility. The less the perceived environmental uncertainty differs from the objective environmental uncertainty, the more consistency the company has. The degree of the consistency (or inconsistency) arises between what the company shows in their perceptions of the external environment and what they show in their efforts to track objective information. Consistency implies a capability of predicting the external environment. For example, Company A has two kinds of solutions, one is “When the customers are active, and they provide a list as they know what they want”; the other is for a blank market, “We will provide the other solution listing all the instruments which are prepared for your lab [the customer]” Company B also integrates the capability of processing objective information and their sense of the accuracy, for example, “They [customers] would propose some suggestions for improving the instrument. [...] If their suggestions are useful, we would make some adjustments [...] The improvement would depend on long term experiments. It is impossible to make changes just after getting their feedbacks.” Considering the evidence from the coding process, it seems that greater consistency is associated with less flexible relationships (see Table IV). Company A and Company C, with a high levels of consistency, show low levels of relationship flexibility; while Company B and Company D, with low levels of consistency, show relatively high levels of relationship flexibility. Overall, these observations suggest that higher consistency and thus a stronger capability of predicting environmental uncertainty would be associated with a lower level of relationship flexibility. In other words, the level of consistency is high enough to make the company believe their judgment and tend to maintain stable relationships. Thus:

\[ P1c. \] The consistency between objective environmental uncertainty and perceived environmental uncertainty has a negative effect on relationship flexibility.

4.3 The effects of environmental uncertainty on logistics flexibility

Both Company A and Company B are in the environmental instrument industry, which is high in objective environmental uncertainty, whereas both Company C and Company D are in the power generation industry, which is low in objective environmental uncertainty. They collect objective information about the external environment by using a report system or a market center mentioned in the interview, for example, “When reports arise that pollution exists somewhere, we can arrive quickly to begin work” (Company A); “Based on e-report of
resources each month and two assessment indexes [resource purchasing and inventory] proposed at the beginning of the year, we can monitor the process of resource management” (Company C); “The market center will determine the category and quantity of the products and then provide orders for coal mines” (Company D). However, under the same level of objective environmental uncertainty, the levels of logistics flexibility of Company A and Company B are different, one is high and the other is low. Similarly, the levels of logistics flexibility of Company C and Company D are different too, one very low and the other high. Thus, there is no clear pattern in how objective environmental uncertainty might affect logistics flexibility:

P2a. The effect of objective environmental uncertainty on logistics flexibility is null.

In the environmental instrument industry, Company A realizes that “The whole industry is driven by policies and regulations, so with the new policy, we just follow it (the policy) no matter what kind of products they ask for” (i.e. high in perceived environmental uncertainty). Thus, Company A is trying to enhance their resource-based capability underlying logistics flexibility in terms of arranging others’ resources flexibly, implementing flexible inventory policies and delivering products and services flexibly. While in the same industry, Company B believes the pollution control instrument industry in China to be very stable as neither their customers nor their competitors has changed since the introduction of the new particulate standard. Thus, they show a low level of perceived environmental uncertainty. Compared to Company A, the level of logistics flexibility is much lower for Company B as they insist that “No matter what kind of changes, our (product category) structure will remain the same as will our customers […] The filter-based monitoring is still used.”

A similar pattern arises in the power generation industry when comparing Company C with Company D. Company C, who perceives a low level of environmental uncertainty, displays relatively rigid logistics activities, whereas Company D, who perceives a higher level of environmental uncertainty, implements flexible delivery and transportation. The reason for the difference may be that the two companies selected in the same industry have quite divergent business philosophies about how top-level managers should respond to the external environment: one translates as “still waters run deep” (Company C); but the other is “motion is absolute, while stillness is relative” (Company D). Here it seems that perceived environmental uncertainty enhances the implementation of logistics flexibility, in that when a company perceives a high level of uncertainty in the external environment, no matter what the objective conditions, they would invest relatively more in logistics flexibility in reliance on their beliefs:

P2b. Perceived environmental uncertainty has a positive effect on logistics flexibility.

According to contingency theory (Donaldson, 2001), the organizational factor’s effect on performance is contingent on environmental elements. Inspired by this theory, we further explore whether the impact of perceived environmental uncertainty on logistics flexibility is dependent on objective environmental uncertainty, that is, the implications of the consistency between objective and perceived environmental uncertainty to logistics flexibility.

We first found that for logistics flexibility, the companies could exert their predicting capabilities. For example, the manager of Company A stated that: “For new products, we have little data to forecast the market. You send the order, and we produce, so there is no inventory. However, for traditional products like UV-spectrophotometers, we know the annual demand in this market, so we would have a certain amount of safety stock. When stock is below this level, we have to produce no matter whether orders exist or not.”

Furthermore, it is interesting to find that the relation between the consistency of perceptions with objective uncertainty and logistics flexibility is opposite between the two groups (see Table IV). For Company A, the level of perceived environmental uncertainty is
consistent with the level of objective environmental uncertainty and its logistics flexibility is high, while Company B which displays a low level of consistency has a low level of logistics flexibility. However, in another industry, with a high level of consistency, Company C has a low level of logistics flexibility; while with a low level of consistency, Company D has a high level of logistics flexibility.

Based on the above opposite implied directional effects, we may conclude that objective environmental uncertainty which is different in the two industries played a moderating role. The underlying logic of a moderating effect points to the argument that the direction of such effect depends on the level of objective environmental uncertainty. When objective environmental uncertainty is low, the effect of consistency on logistics flexibility is still negative. In contrast, when objective environmental uncertainty is high, the effect changes into positive, which means that predicating capability and logistics flexibility are both necessary under this condition. We thus propose the following competing proposition:

\[P2c. \text{Objective environmental uncertainty moderates the effect of the consistency between objective environmental uncertainty and perceived environmental uncertainty on logistics flexibility.}\]

### 4.4 The change of risks

According to the literature review, supply chain flexibility has been shown to lower the level of risk. Thus, we also coded the risk level of each company using secondary data as shown in Table V. Based on the definition of risk, we mainly coded the data from 2012 to 2017 to show the trend of risk changes. For Company A and Company B that are not listed companies, we tried to find the information about their taxpaying credit, successful bids, and patents.

<table>
<thead>
<tr>
<th>Company</th>
<th>Supply chain flexibility</th>
<th>Risk level</th>
<th>Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>High logistics flexibility</td>
<td>Low</td>
<td>The company taxpaying credit was A level in 2014 and 2016. The number of successful bids was 102 in 2005, 55 in 2016 and 26 in 2017. They invested two instrument companies in 2012, one in 2014 and one in 2017. The number of patents was 6, 18, 15, 17, 18, and 34 from 2012 to 2017.</td>
</tr>
<tr>
<td>Company B</td>
<td>High relationship flexibility</td>
<td>Low</td>
<td>The company taxpaying credit was A level in 2014 and 2016. The number of successful bids was 82 in 2016 and 32 in 2017. Especially, they got the maintenance work of 97 atmosphere automatic monitoring stations in villages in Hubei province. They invested two companies in environment protection industry in 2013, two in 2014 and one in 2017. The number of patents was 7, 4, 3, 15, 1, and 1 from 2012 to 2017.</td>
</tr>
<tr>
<td>Company C</td>
<td>Low logistics and relationship flexibility</td>
<td>High</td>
<td>According to annual financial reports, the main business income was 250,290 million RMB in 2012, 283,797 million RMB in 2013, 248,280 million RMB in 2014, 177,069 million RMB in 2015 and 183,125 million RMB in 2016. In the regression of year on income, the slope is (-0.820), and the std. error is 9,698.</td>
</tr>
<tr>
<td>Company D</td>
<td>High logistics and relationship flexibility</td>
<td>Low</td>
<td>According to annual financial reports, the main business income was 17,497.128 million RMB in 2012, 18,826.728 million RMB in 2013, 20,447.151 million RMB in 2014, 20,196.67 million RMB in 2015, 18,866.153 million RMB in 2016. In the regression of year on income, the slope is 0.544, and the std. error is 3,654. In particular, the company began to evaluate risks and publish a risk report in 2014, which represents that except for market and policy changing risks, the other risks such as approval risk, nature risk, pro-environment policy risk, capital risk and exchange risk are all steady.</td>
</tr>
</tbody>
</table>

Table V. The change of risks
external investments and patents. For listed companies (Company C and Company D), we could collect their financial data from annual reports, so we calculated the level of risk for them.

As shown in Table V, the credit levels of Company A and Company B were very high from 2014 to 2016. Although the number of successful bids was changing, they still could get many projects. Company B, in particular, got the maintenance work of 97 atmosphere automatic monitoring stations in villages in Hubei province. In addition, both of them invested the other companies in their own industry each year, which indicates their great financial strength as well as the capability of risk diversification. Finally, the number of patents in Company A has been steadily growing, while for Company B, the number has been decreasing in recent years.

As shown in Table V, the main business income of Company C has been decreasing from RMB28,379.7bn in 2013 to RMB18,312.7bn in 2016. According to the calculation of risk, the previous five years' incomes were treated as the dependent variable against time (from 2013 to 2016) as the independent variable. The results show that the incoming is decreasing dramatically in recent years. In contrast, the main business income of Company D does not change significantly, from RMB174.97bn in 2012 to RMB188.66bn in 2016. Further, the regression results show that the volatility of the income is much lower than Company C, which, in turn, represents a lower level of risk. In the risk report of Company D in 2014, it also illustrates that risks such as approval risk, nature risk, pro-environment policy risk, capital risk and exchange risk are all steady.

Combined with the level of supply chain flexibility, we thus propose the following propositions:

\[ P3a. \] The higher the level of logistics flexibility is, the lower the level of risks will be.

\[ P3b. \] The higher the level of relationship flexibility is, the lower the level of risks will be.

5. Discussions and implications

Motivated by the question of how firms implement their flexibility strategies in response to environmental uncertainty in their SCRM, this paper conducted a case study of four companies from two industries in China. We interviewed two companies from the environmental instrument industry and the other two from the power generation industry in China, coded and compared their objective environmental uncertainty, subjective environmental uncertainty, consistency between two types of environmental uncertainty, relationship flexibility strategy and logistics flexibility strategy, among other characteristics of these case companies.

A major contribution of this study is the differentiation between the objective environmental uncertainty and perceived environmental uncertainty, which enables exploration of whether and how these two types of environmental uncertainty as well as the (in)consistency between them affect a firm’s flexibility strategies in its supply chain. Our results showed that it was the consistency between objective and perceived environmental uncertainty (as an indicator of firms’ ability of risk prediction) that may have an effect on firms’ flexibility strategies which then have a positive effect on supply chain risk mitigation.

Specifically, a higher (lower) level of relationship flexibility was observed from companies with a lower (higher) consistency between the objective and perceived environmental uncertainty. The logic is that as the environmental uncertainty perceived by the managers deviates from the objective state, relationship flexibility as a flexible norm would be enhanced, most plausibly so as to reduce rising opportunism in the bilateral relationship. In contrast, on logistics flexibility, this negative effect of the consistency
between objective and perceived environmental uncertainty was only observed for the companies from the power generation industry with a low level of objective environmental uncertainty. For the companies from the environmental instrument industry with a high level of objective environmental uncertainty, a reversed effect was observed, namely, the more inconsistent a firm’s perception with the objective environmental uncertainty, the higher logistics flexibility was observed. In addition, a higher (lower) level of supply chain risk reduction was observed from companies with a higher (lower) level of relationship flexibility or logistics flexibility, which is consistent with past research on the effect of supply chain flexibility in reducing supply chain risk (Tang, 2006; Tomlin, 2014).

Based on the findings, we have developed propositions that the consistency between objective and perceived environmental uncertainty has a symmetrically negative influence on relationship flexibility; the effect of the consistency between objective and perceived environmental uncertainty on logistics flexibility is moderated by the objective environmental uncertainty; and both the relationship flexibility and the logistics flexibility have positive effects on supply chain risk mitigation.

On the one hand, these propositions extend contingency theory by highlighting the importance of the consistency between objective and perceived environmental uncertainty. While existing contingency literature usually focuses on the objective organizational factors such as corporate strategy and organizational structure, our study provides that contingency effect is applicable to perceived environmental uncertainty, a subjective factor. In this sense, this study extends the applicability of contingency theory. On the other hand, this study contributes to the understanding of how supply chain flexibility mitigates supply chain risk: it not only extends the scope of supply chain flexibility from inter-firm relationship flexibility (e.g. buyer–supplier relationship, Sánchez and Pérez, 2005; Tomlin, 2014) to a two-dimensional setting of supply chain flexibility, including both intra-firm logistics flexibility and inter-firm relationship flexibility, but also extends the scope of supply chain risks from supply, demand, process or network risks (that mainly due to supply-demand imbalances) to a more general operational setting, including credit risk, market risk, investment and capital risk, etc.

The managerial implication of this study is twofold. On the one hand, according to our findings on relationship flexibility, it is indicated that regardless of the environmental conditions, only if a large bias exists in the firm’s perceptions of the environmental uncertainty from the objective state (e.g. when the firm has poor ability of risk prediction) will the focal firm tend to maintain flexible relationships with their partners. Conversely, if the managers’ perception is consistent with the objective environmental uncertainty, they tend to maintain more rigid relationships. Thus, managers should understand that in the SCRM, a firm’s strategy of relationship flexibility is more a response to the consistency between its perceived and objective environment conditions (e.g. its own ability of risk prediction), rather than a response to the objective/perceived environmental uncertainty \textit{per se}. Further, if a company puts efforts on increasing the consistency between the two types of environmental uncertainty (for instance, by investing in the database or forecasting systems), then this will imply a reduction in the costs associated with relationship flexibility in the near future as the company tends to gradually adopt more rigid relationships with its supply chain partners.

On the other hand, our findings on logistics flexibility imply that for companies in a turbulent environment (with a high level of objective environmental uncertainty), a company which has a higher consistency in its perception of environmental uncertainty (with the objective state) tends to implement a strategy of lower logistics flexibility; however, in a less unpredictable and risky environment, the consistency between the objective and perceived environmental uncertainty may not affect the firms’ strategies of logistics flexibility. Therefore, managers should be aware that, in an environment with a
high level of objective uncertainty, investing in the consistency between two types of environmental uncertainty (e.g. improving risk prediction capability) will imply a later reduction in costs associated with logistics flexibility; but this may not be true in an environment/industry with a low level of objective environmental uncertainty.

There are some clear limitations to this study. First, due to the obstacles of collecting firm-level data in China, this study adopted a multi-case study of four companies. Future studies could try to get a larger and more random sample. Second, the inconsistency between perceived and objective environmental uncertainty was calculated as a difference, yet there could be other methods such as using an absolute residual to measure misfit (Zajac et al., 2000). Finally, this study tried to distinguish between perceived and objective environmental uncertainty, but only macro-level uncertainty rather than micro-level is concerned (Flynn et al., 2016). Future research could have a discussion on the role of decision makers’ psychological issues such as their tolerance for uncertainty and prior experience.

References


Appendix. Interview guide

Background
Company: ____________________________
Division: ______________________________
Job: __________________________________
Years in Position: ______________________

Company Introduction
Firm size, market share, business model, main products and competitive advantages

Environmental Conditions
What kind of industry are you in? Could you please give a brief description of this industry?
In the last five years, have there ever been any changes in customer demand? If yes, please share an example or two.
Probing: Such as preferences for product features, preferences for brands, preferences about product quality/price, preferences about volume and composition, etc.?
In the last five years, have there ever been any changes in competitive activity? If yes, please share an example or two.
Probing: Such as pricing fluctuation, sales and promotional strategies, value-added service, etc.

Flexibility Strategies
When changes have taken place in the environment, what kinds of logistics strategies did you undertake?
Probing: Did you increase storage capacity, open more warehouses, or try to hold the inventory level stationary? Did you change the order fulfillment time, customize assortments and delivery, increase value-added services? Did you increase transportation capacity, use more combinations of transportation modes? Explain briefly.
When changes took place in the environment, what kinds of coordination strategies did you undertake?
Probing: Did you modify the agreement with your supply chain members or try to hold to the original terms? Did you initiate offers to support your supply chain members? If yes, please share an example or two.
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Decision modeling of risks in pharmaceutical supply chains

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Abstract

Purpose – Managing risks is becoming a highly focused activity in the health service sector. In particular, due to the complex nature of processes in the pharmaceutical industry, several risks have been associated to its supply chains. The purpose of this paper is to identify and analyze the risks occurring in the supply chains of the pharmaceutical industry and propose a decision model, based on the Analytical Hierarchy Process (AHP) method, for evaluating risks in pharmaceutical supply chains (PSCs).

Design/methodology/approach – The proposed model was developed based on the Delphi method and AHP techniques. The Delphi method helped to select the relevant risks associated to PSCs. A total of 16 sub risks within four main risks were identified through an extensive review of the literature and by conducting a further investigation with experts from five pharmaceutical companies in Bangladesh. AHP contributed to the analysis of the risks and determination of their priorities.

Findings – The results of the study indicated that supply-related risks such as fluctuation in imports arrival, lack of information sharing, key supplier failure and non-availability of materials should be prioritized over operational, financial and demand-related risks.

Originality/value – This work is one of the initial contributions in the literature that focused on identifying and evaluating PSC risks in the context of Bangladesh. This research work can assist practitioners and industrial managers in the pharmaceutical industry in taking proactive action to minimize its supply chain risks. To the end, the authors performed a sensitivity analysis test, which gives an understanding of the stability of ranking of risks.

Keywords Bangladesh, Analytical hierarchy process, Supply chain management, Risks, Delphi method, Pharmaceutical supply chain

Paper type Research paper

1. Introduction

Risk is represented in terms of uncertain event, which possesses the probability of occurrence of unfavorable outcomes like late delivery, financial burdens, business loss, etc. (Holton, 2004; Mangla et al., 2016). Risk exists in various fields of research like insurance, finance, manufacturing, healthcare, supply chain management, etc. (Kouvelis et al., 2006; Kiczyk, 2008; Mangla et al., 2015a; Vian et al., 2017). In today’s scenario, organizations are becoming more vulnerable in their supply chain due to irregularities of
material supply, product demand, skills and equipment requirements (Finch, 2004; Enyinda et al., 2009; Gandhi et al., 2016). Therefore, managing of risk has become important to tackle such kinds of disturbances from a supply chain context (Christopher and Lee, 2004; Tuncel and Alpan, 2010; Mangla et al., 2016). Managing risk can be a challenging part in pharmaceutical supply chain (PSC) due to its complex and dynamic network structure (Jaberidoost et al., 2013). PSC is responsible for a smooth flow of medicine to reach the customers (Manuj and Mentzer, 2008; Jaberidoost et al., 2015). Being a significant element of the health scheme, PSC covers various activities like purchasing and procurement of raw materials, manufacturing, 3P (third party) for logistics and distribution, marketing, financing, sales and promotions (Wagner et al., 2011; Vian et al., 2017).

Pharmaceutical industry plays a significant role in providing medicines and saving human life. In this sense, any risk affecting the PSC could affect the efficiency of health system and disrupt the supply of medicines (Hung et al., 2005; Tazin, 2016). To deal with such vulnerabilities, it is important to examine the related risks and to reduce their occurrence to ensure the best practices in the PSC for quality ingredient of drug and flexibility in the business. An adequate understanding of risks can help pharmaceutical industries to minimize costs and liability, avoid waste, and thus, results in enhanced efficiency of the supply chain (Kwak and Dixon, 2008; Rogachev, 2008). Notably, over the past few years, researchers addressed the theme of risk assessment in pharmaceutical sector and the majority of studies conducted by considering a particular supply chain activity, such as outsourcing and off shoring (Enyinda et al., 2009; Mokrini, Dafaoui, Berrado and El Mhamedi (2016), Mokrini, Kafa, Dafaoui, El Mhamedi and Berrado (2016)). This work aims to evaluate risks for the PSC by taking a holistic view. In addition, the present study aims to address the following questions:

*RQ1*. What are underlying supply chain risks in the PSC context?

*RQ2*. How the identified risks are modeled to know their priority?

This work is one of the initial contributions in the literature that focused on identifying and evaluating PSC risks in the context of Bangladesh. The first aim of this work is to select the most suitable risks in PSC in Bangladesh. The pharmaceutical industry plays a very important role in Bangladesh economy as the demand of medicine in its local market increased due to improved level of people awareness about health, higher income rate and increased governmental interventions (Ahamed, 2012). The second aim of this study is to evaluate the identified risks for determining their priority. For this purpose, Analytical Hierarchy Process (AHP) tool is used (Luthra, Sachin Mangla, Venkatesh and Jakhar, 2017).

The rest of this paper is structured as follows. Section 2 provides a comprehensive literature review. Section 3 illustrates the problem addressed in this research work. The solution methodology is provided in Section 4. Section 5 offers data analysis and results for the study. The sensitivity analysis is conducted in Section 6. Discussions of results and research implications are given in Section 7. Finally, Section 8 concludes the paper and provides limitations and scope for future work as well.

2. Literature review

This section present the literature related to PSC and risks in PSC context. At the end of this section, research gaps are provided.

2.1 Pharmaceutical supply chain

Supply chain involves movement of goods/information/money to satisfy customer requirements and consists of various entities – producers and suppliers, transporters,
warehouses, retailers and stakeholders (Dubey and Sai Kumar, 2007). The PSC is somewhat different from the other supply chains of physical goods because of its urgency, importance, storage and transportation safety, regulation, etc. (Bigdeli et al., 2013). PSC covers drug research and development, production, distribution and application through wide verities of healthcare facilities and additional businesses that help effective functioning of these different stages (Hulbert et al., 2008; Adam, 2013; Jaberidoost et al., 2015). Ricci (2007) stated the contribution of initiative of pharmaceutical industries in controlling the distribution function through improved communicating modes, which saves the human life from errors or defects occurred during repackaging or relabeling.

As the pharmaceutical commercial center goes up against overwhelming difficulties with different partners guaranteeing the pharmaceutical items on a reasonable prices, and thus, a strategic planning is important (Holdford, 2005). In addition, the boundary lines between an organization’s inner and its outer operations, from the study of Graves et al. (2009) are becoming progressively fuzzy. Pharmaceutical products are relevant to human life that’s why PSC is more important than any other supply chain network. Therefore, it needs proper execution in every branch of supply chain network to give better customer service and quality products. Chopra and Meindl (2014) pointed out that PSC should maintain regulatory compliance for ensuring better product quality. Moreover, this includes strong information sharing facility to facilitate more efficient supply chain network and fulfills the consumer’s requirements. PSC network is unique due to the problems of data complexity and challenging supply chain adequacy, which needs careful attention to resolve these issues. Privett and Gonsalvez (2014) highlighted several challenges associated with the global PSC including inventory management, lacking demand information, human resource dependence and warehouse management. In addition, pharmaceutical companies have to manage its complex supply chains network due to involvement of many products, markets, processes and intermediaries in the network (Jaberidoost et al., 2013). A brief summary of recent contributions made by different scholars in area of PSC is provided in Table I.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Contributions</th>
<th>Methodology/Context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enyinda et al. (2009)</td>
<td>Proposed a framework for assessing outsourcing risks in global pharmaceutical supply chains</td>
<td>AHP</td>
</tr>
<tr>
<td>Jaberidoost et al. (2015)</td>
<td>Developed risk assessment framework of Pharmaceutical supply chain in the context of Iran</td>
<td>AHP</td>
</tr>
<tr>
<td>Ouabouch and Amri (2013)</td>
<td>Assessed logistics supply chain risks in pharmaceutical industry</td>
<td>A probability impact matrix-based methodology</td>
</tr>
<tr>
<td>Aigbogun et al. (2014)</td>
<td>Developed a framework to enhance supply chain resilience in the context of Malaysian pharmaceutical industry</td>
<td>Conceptual model</td>
</tr>
<tr>
<td>Elleuch et al. (2014)</td>
<td>Proposed a combined descriptive and application-based approach for risks in pharmaceutical supply chain</td>
<td>Combined descriptive and application-based approach</td>
</tr>
<tr>
<td>Mokrini, Dafaoui, Berrado and El Mhamedi (2016)</td>
<td>Proposed a risk assessment approach for outsourcing logistics in pharmaceutical supply chains</td>
<td>ELECTRE TRI</td>
</tr>
<tr>
<td>Mokrini, Kafa, Dafaoui, El Mhamedi and Berrado (2016)</td>
<td>Evaluated the outsourcing risks in the pharmaceutical supply chain.</td>
<td>Fuzzy AHP-PROMETHEE</td>
</tr>
<tr>
<td>Lucke and Seifert (2017)</td>
<td>Focused on building resilience in pharmaceutical supply chains by considering inventory, capacity and dual sourcing aspects</td>
<td>A mathematical model</td>
</tr>
<tr>
<td>Pariazar et al. (2017)</td>
<td>Studied supply chain design issues to trade off and minimize risks in pharmaceutical and food supply chains</td>
<td>A two-stage stochastic programming model</td>
</tr>
</tbody>
</table>

Table I. Summarizing the recent contributions in area of PSC
For the pharmaceutical industry, it needs special attention because flow of medical products (i.e. medicine, medical components) are managed through the supply chain network in terms of delivery at right time, right place and to the right customers to meet their significant needs and requirements (Enyinda et al., 2009). A root cause of any inadequacy of PSC network is lack of coordination among supply chain members and stakeholders, which may lower the overall efficiency. Necessary measures should be taken to improve pharmaceutical based products delivery in regions that need it to make the global health challenge easier to take on and to save lives.

2.2 Risks in the context of pharmaceutical supply chain

Access to medicines is a human right, and one of the prime concerns of the healthcare systems. The supply chain connecting pharmaceutical industry is a prime part of the healthcare systems in distributing drugs to the community. Supply chain risks can waste resources as well as deteriorate PSC performance. Therefore, proper identification and analysis of risk are useful in formulating strategies to minimize the risks in the PSC (Adam, 2013; Hulbert et al., 2008; Jaberidoost et al., 2013). Risk management in the pharmaceutical industry context is getting increased attention. Because medicine products are profoundly controlled items and comes under the legitimacy of public regulatory authorities (Craighead et al., 2007; O’Connor et al., 2016). Moreover, supply of medicines involves higher more uncertainties and vulnerabilities due to economic, social and political instability in developing countries (Enyinda et al., 2009; Jaberidoost et al., 2015).

Managing risks in supply chains can lead to high performances and can reduce supply chain vulnerability and uncertainties through suitable plans and strategies (Breen, 2008; Mangla et al., 2015a). Researchers suggested that for risk management, organizations should follow a formal structure which helps them to identify supply chain risk, quantifying risk and finally reducing risk (Frosdick, 1997; Khan and Burnes, 2007; Mangla et al., 2016).

Based on previous studies, 16 risks in PSC context are selected. These risks were further confirmed through expert’s feedback. In addition, the identified risks were divided into four main risks, given as supply-related risks, operational-related risks, financial-related risks, and demand-related risks. The simplified meaning of the identified risks along with their sources is provided in Table II.

2.3 Research gaps and problem definition for the research

PSCs has become imperative segments of the health system in drug supply, especially in nations where the principle medical products are given by nearby pharmaceutical organizations (Zhang et al., 2008; Rossetti et al., 2011; Uthayakumar and Priyan, 2013). The pharmaceutical industry is also facing tremendous uncertainty and fluctuations in demand, which may challenge its business sustainability in both local and international markets. The pharmaceutical industry are also facing various relevant supply chain issues, like shortage of raw materials, quality problem of the products, short product life cycle, sustainable supplier failure and seasonal demand of products (Craighead et al., 2007; O’Connor et al., 2016; Luthra, Sachin Mangla, Venkatesh and Jakhar, 2017). Requirements of high technology are also an important issue being faced by organizations in a PSC context (Mahendran et al., 2011). Any problematic issue or disturbance influencing the pharmaceutical organizations’ supply chain structure may not only hamper the supply of medicine products but also affect the efficiency of health system (Jaberidoost et al., 2015). Several works have been performed by different scholars in PSC area in recent years, specifically on understanding of idea, production and distribution system, availability/flow of medicines and development of policies (Rossetti et al., 2011; Jaberidoost et al., 2013; Uthayakumar and Priyan, 2013; Abdallah, 2013). The present work is an original effort.
that examines the risks in PSC in the context of Bangladesh. In Bangladesh, the pharmaceutical industry has a major role in its economic growth. Bangladesh exports active pharmaceutical ingredients along with a wide variety of pharmaceutical items to several countries, such as Myanmar, Sri Lanka and Kenya (Tazin, 2016). Besides, pharmaceutical companies are experiencing huge competition in Bangladesh. Above all, pharmaceutical companies are facing supply chain disruptions due to technological revolution, organizational policy change, and uncertain market environment. Although, there is significant advancement in infrastructure, information and communication technology in pharmaceutical sector; yet, the industry is confronting different risks in supply chain (Jaberidoost et al., 2015). Therefore, managing risks in PSC has become a key focus of this industry (Yu et al., 2010). Analyzing risks is becoming a highly focused and increasingly adopted activity among organizations targeting to ensure a smooth and trouble free business (Mangla et al., 2015a). To deal with these research gaps and problem defined, the highlights of the contributions made by this research are given as:

- Identifying the key PSC risks in the context of Bangladesh using literature and expert’s inputs under Delphi technique. This will give managers an understanding on the different risks existing in this sector.
- Evaluating the identified risks to know their priority using AHP. This will give an understanding on significant risks in managing the PSCs.

### 3. Solution methodology

In this research work, the Delphi and AHP techniques have been used as solution methodology. The reasons for combining Delphi and AHP are (Chuang et al., 2013; Kim et al., 2013):

1. The combined Delphi–AHP tool is a systematic method of decision making, which offers logical means to list the risks in PSC scenario.

<table>
<thead>
<tr>
<th>Main risks</th>
<th>Sub risks</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply-related risks (S)</td>
<td>Fluctuation in imports arrival (S1)</td>
<td>Amin (2015), Mokrini, Dafaoui, Berrado and El Mamed (2016)</td>
</tr>
<tr>
<td></td>
<td>Lack of information sharing (S2)</td>
<td>Jaberidoost et al. (2013), Yousefi and Alibaba (2015)</td>
</tr>
<tr>
<td></td>
<td>Key supplier failure (S3)</td>
<td>Zsidisin et al. (2004), Blackhurst et al. (2008), Wagner et al. (2009)</td>
</tr>
<tr>
<td></td>
<td>Non-availability of materials (S4)</td>
<td>Breen (2008), Mahendran et al. (2011), Ketkar and Vaidya (2012)</td>
</tr>
<tr>
<td>Operational-related risk (O)</td>
<td>Machine, equipment or facility failure (O1)</td>
<td>Mahendran et al. (2011), Finch (2004)</td>
</tr>
<tr>
<td></td>
<td>Quality risk (O2)</td>
<td>Mahendran et al. (2011), O’Connor et al. (2016)</td>
</tr>
<tr>
<td></td>
<td>Storage contamination risks (O3)</td>
<td>Mahendran et al. (2011), Brettler (2015)</td>
</tr>
<tr>
<td></td>
<td>Power failure (O4)</td>
<td>Finch (2004)</td>
</tr>
<tr>
<td>Financial-related risks (F)</td>
<td>Increase in freight charges (F1)</td>
<td>Goff (2012)</td>
</tr>
<tr>
<td></td>
<td>Dynamic foreign exchange rates (F2)</td>
<td>Blome and Schoenherr (2011), Torabi et al. (2016)</td>
</tr>
<tr>
<td></td>
<td>Bank interest rate fluctuation (F3)</td>
<td>Blackhurst et al. (2008), Blos et al. (2009), Tummala and Schoenherr (2011)</td>
</tr>
<tr>
<td>Demand-related risk (D)</td>
<td>Financial restriction (F4)</td>
<td>Mangla et al. (2015a)</td>
</tr>
<tr>
<td></td>
<td>Demand forecasting errors (D1)</td>
<td>Breen (2008), Candan et al. (2014)</td>
</tr>
<tr>
<td></td>
<td>Uncertainty in market (D2)</td>
<td>Enyinda et al. (2009), Mahendran et al. (2011)</td>
</tr>
<tr>
<td></td>
<td>Bullwhip effects (D3)</td>
<td>Metters (1997), Craighead et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>Competitive risks (D4)</td>
<td>Mangla et al. (2015a)</td>
</tr>
</tbody>
</table>
The combined Delphi–AHP allows knowing the most significant risks in managing the risks in PSC scenario.

The flow chart of this research is presented in Figure 1. The Delphi and AHP methods are detailed in the subsequent sub-sections.

3.1 Delphi method

The Delphi research method is a rational research technique in which data are collected from group of experts with the help of multiple sessions/questions (Chuang et al., 2013; Lummus et al., 2005). It is very effective technique to evaluate data in which experts share their opinion, knowledge and experience until they reach to a mutual consent (Markmann et al., 2013; Nowack et al., 2011; Soon et al., 2012; Ilic et al., 2015, 2017). This technique is one of the popular tools in identifying and evaluating issues related to the multi criteria decision making problems. In this work, Delphi method is used to finalize the most relevant risks in PSC. There is no specific limitation of considering experts to evaluate data. Normally, 10 to 30 experts opinion are suggested to be sufficient to ensure the best result by reaching a
consensus among experts (Murry and Hammons, 1995). In this research, we formed a group of 10 industrial and field experts to select PSC risks. Consequently, we utilized AHP technique to evaluate risks with the help of experts input.

### 3.2 Analytical Hierarchy Process (AHP)

AHP is a decision analysis tool proposed by Prof. Thomas L. Saaty (1980). With the help of AHP, difficult problems are evaluated very easily (Luthra et al., 2015). The complex decision problems are converted into a hierarchical structure consisting of multiple levels, like goal, criteria, sub-criteria (Dey and Cheffi, 2013; Govindan et al., 2014; Madaan and Mangla, 2015). AHP allows policy makers to have optimal decisions in an organizational context. The input for the AHP can be picked from subjective assessment like review, interview and preference. AHP is used as a better decision making tools compared to ANP, TOPSIS, VIKOR, ELECTRE due to its wide acceptability and applicability, less pair wise comparisons, and simplicity in use (Topçu et al., 2011; Luthra, Govindan, Kannan, Mangla and Garg, 2017). However, AHP may involve some small inconsistency in human judgment (Russo and Camanho, 2015). Hence, AHP has been criticized because it sometimes results in an unbalanced scale of judgment and ranking. In this research, we used AHP to evaluate PSC risks to know their priority. We also summarized the application of AHP in supply chain risk assessment in Table III.

The basic steps of AHP (Schoenherr et al., 2008; Luthra, Govindan, Kannan, Mangla and Garg, 2017) are explained in below:

1. Fix the aim of present study: evaluating the risks to examine their priority ranking in the PSC is fixed as the goal of this study.

2. Construct pairwise comparisons matrix: pairwise comparison matrix is constructed with the help of expert’s feedback from assigned pharmaceutical companies. The pair wise comparisons matrix (A) among the risk is constructed with the help of a nine-point Saaty’s scale (Saaty, 1980). The element \(a_{ij}\) of the matrix A is the relative importance of \(i\)th risk factor with respect to \(j\)th risk factor. The representation is done like the following: \(A = [a_{ij}]\), each entry in matrix A is positive \((a_{ij} > 0)\) (Jaberidoost et al., 2015).

3. Calculation of the eigen values and eigen vectors and priority weights: the formulated pair wise comparison matrices are then used to calculate the eigen values and eigen vector. Next, the priority weights of the listed risks are calculated.

4. Computation of the consistency ratio (CR): the CR checks the consistency of formulated pair wise comparisons matrices. CR is calculated with the help of following mathematical equation, \(CR = CI/RI\), where, consistency index (CI) can be calculated by \(CI = \) Maximum Eigenvalue–\(n/n−1\). The random consistency index (RI) value depends upon value of \((n)\) as shown in Table IV. The value of CR should be less than 0.10 to have better level of consistency (Madaan and Mangla, 2015).

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Author</th>
<th>Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gaudenzi and Borghesi (2006)</td>
<td>Overall managing risks in the supply chain</td>
</tr>
<tr>
<td>2</td>
<td>Wu et al. (2006)</td>
<td>Inbound supply risk analysis</td>
</tr>
<tr>
<td>3</td>
<td>Schoenherr et al. (2008)</td>
<td>Assessing supply chain risks for a US manufacturing company</td>
</tr>
<tr>
<td>4</td>
<td>Wang et al. (2010)</td>
<td>The risk research of ecological supply chain</td>
</tr>
<tr>
<td>5</td>
<td>Sharma and Bhat (2012)</td>
<td>Assess the supply chain risk</td>
</tr>
<tr>
<td>6</td>
<td>Badea et al. (2014)</td>
<td>Investigating risk in collaborative supply chain</td>
</tr>
<tr>
<td>7</td>
<td>Dong and Cooper (2016)</td>
<td>Supply chain risk assessment framework</td>
</tr>
<tr>
<td>8</td>
<td>Prostean et al. (2014)</td>
<td>Risk variables in wind power supply chain</td>
</tr>
<tr>
<td>9</td>
<td>Luthra, Sachin Mangla, Venkatesh and Jakhar (2017)</td>
<td>Prioritization and management of risks in sustainable supply chain</td>
</tr>
</tbody>
</table>
4. Data analysis and results
Data analysis and results are provided in the subsequent sections.

4.1 Data collection
In this research, data are collected through two phases: Phase 1, identification of most relevant PSC risks with the help of industrial and field experts and Phase 2, prioritizing the identified risks with the help of expert’s inputs.

In this work, case companies were selected based on purposive sampling method rather than statistical sampling (Glaser and Strauss, 1967). In the purposive sampling method, the case companies are not selected randomly (Eisenhardt, 1989; Maalouf and Gammelgaard, 2016; Bai et al., 2017). The five pharmaceutical companies operating in Bangladesh were selected due to their immense interest to examine and manage the risks in their supply chain context. Next, ten industrial and field experts were selected from the listed five pharmaceutical companies. The selected experts are highly competent on PSC and supply chain risk management. We collected expert’s feedback through several rounds of personal interviews, e-mail communication and telephonic discussion through questionnaire as provided in Appendix 1. An interview protocol was prepared based on a set of questionnaire with focusing several themes. The profile of experts along with the pharmaceutical company details contacted for data collection in this work is shown in Table V.

Next step was to collect the data needed for addressing the goals of this work. The two phased data collection is explained as follows.

<table>
<thead>
<tr>
<th>Professionals</th>
<th>Years of experience</th>
<th>Name of company, products</th>
<th>Company size (employees, annual sales turnover for FY-2015)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. General manager</td>
<td>18 years</td>
<td>XYZ1 pharmaceutical, medicine</td>
<td>Area: 22-acre, employees-3,000, annual sales turnover-BDT 12,965.51m (January–December, 2015)</td>
</tr>
<tr>
<td>2. Supply chain executive</td>
<td>16 years</td>
<td>XYZ2 pharmaceutical, medicine</td>
<td>Area: 6.89-acre, employees-3,500, annual sales turnover-BDT 12,965.51m</td>
</tr>
<tr>
<td>3. General manager</td>
<td>20 years</td>
<td>XYZ3 pharmaceutical, medicine</td>
<td>Number of products-738, employees-7,174, annual sales turnover-BDT 41,678.78m (2015–2016)</td>
</tr>
<tr>
<td>4. Supply chain executive</td>
<td>15 years</td>
<td>XYZ4 pharmaceutical, medicine</td>
<td>Area: 8.03-acre, employees-6,000, total annual sales, volume above $100m</td>
</tr>
<tr>
<td>5. General manager</td>
<td>17 years</td>
<td>XYZ5 pharmaceutical, medicine</td>
<td>Area: 9.03-acre, employees-4,334, annual sales turnover-BDT 12,880.9m (during January–December, 2015)</td>
</tr>
<tr>
<td>6. Supply chain executive</td>
<td>15 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. General manager</td>
<td>19 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Supply chain executive</td>
<td>17 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. General manager</td>
<td>18 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Supply chain executive</td>
<td>16 years</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table IV. Random consistency index value

<table>
<thead>
<tr>
<th>N</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI</td>
<td>0</td>
<td>0</td>
<td>0.58</td>
<td>0.9</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.49</td>
</tr>
</tbody>
</table>
4.2 Finalizing of the most relevant PSC risks using Delphi method

Total 16 risks falling into four main risks were primarily identified through the literature review. To approve the identified risks, the industrial and field experts were requested for their feedback and asked to include or erase any risk relevant to the existing PSC in the context of Bangladesh. The responses from experts were gathered to finalize the risks. The experts agreed that the four main risks and 16 sub risks are most relevant for PSC in Bangladesh. The simplified meaning of listed risks is also provided upon discussion with experts as given in Appendix 2.

4.3 Evaluation of the PSC risks by determining their priority using AHP

In this step, the finalized risks were prioritized using AHP with the help of expert’s inputs. A hierarchical structural is constructed using expert inputs (Figure 2).

This hierarchical structural figure comprises of three different levels: evaluating the supply chain risks in pharmaceutical sector (Level-1), 4 main risks (Level-2) and 16 sub risks (Level-3).

The pair wise comparisons relation matrices are formed for both the major risks and the sub risks using experts’ inputs through provided Saaty scale. With the help of experts feedback, at first pair wise comparison relation matrix for the main risks is formulated and then we calculated the priority weights and ranking for each risk (see Table VI).

Likewise, the pair wise comparison relation matrices for sub risks under each main risks are formulated and their corresponding priority weights are calculated (for details see Appendix 3).

The pair wise comparison matrices are used to determine the relative importance of weights and global importance of weights and their rank are evaluated in Table VII. Global weights are computed by multiplying relative weights of main risks with relative weights of sub risks and then global ranking is determined accordingly.

Based on Table VII, it is clear that supply-related risk obtained the highest priority, which is followed by operational risk, financial risk and demand-related risk. In this research work, the sub risk “machine, equipment or facility failure (O1)” has got the top priority in risk assessment. Bullwhip effects under the category of demand-related risk gets the last position in evaluation of supply chain risk.

![Figure 2. Hierarchical structure of evaluation of PSC risk](image-url)
5. Discussions of findings

According to Table VII, the ranking of main risks of PSC is as follows: supply risks > organizational risks > financial risks > demand risks. The global ranking of sub risks is also established based on their respective global weights (see Table VII). In this research work, supply-related risk holds the first priority in ranking and thus indicates that this risk should be addressed with highest priority. Supply-related risk can be explained as the risk which occurs during supplying the materials (Amin, 2015; Mokrini, Dafaoui, Berrado and El Mhamedi, 2016; Mangla et al., 2015b). In this main risk, there are four sub risks which are fluctuation in imports arrival, lack of information sharing, key supplier failure and non-availability of materials. According to findings, fluctuation in imports arrival gets the first rank in their ranking. The delay or fluctuations of imports arrival heavily hamper the supply chain process as the regular flow gets disrupted if the raw materials and other components which are exported from outside the country. Therefore, pharmaceutical companies need to concentrate in this issue. Non-availability of materials risk holds the second position thus indicates non-availability of materials can hamper the regular production rate. So decision maker should give attention to ensure materials for regular production. Lack of information sharing and key supplier failure carry third and fourth position subsequently in their ranking.

Operational-related risk comes next to supply risks. Operational risk occurred due to machine, equipment or facility failure, quality risk, storage contamination risks and power failure. Therefore, top management should give attention to minimize such risks to improve operational performance.

<table>
<thead>
<tr>
<th>Risks</th>
<th>S</th>
<th>O</th>
<th>F</th>
<th>D</th>
<th>Relative weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply-related risk</td>
<td>0.3618</td>
<td>0.3270</td>
<td>0.1635</td>
<td>0.1477</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub risks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fluctuation in imports arrival</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.4262</td>
<td>1</td>
</tr>
<tr>
<td>Lack of information sharing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1740</td>
<td>3</td>
</tr>
<tr>
<td>Key supplier failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1463</td>
<td>2</td>
</tr>
<tr>
<td>Non-availability of materials</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.2534</td>
<td>2</td>
</tr>
<tr>
<td>O</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machine, equipment or facility failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.5166</td>
<td>1</td>
</tr>
<tr>
<td>Quality risk</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.2830</td>
<td>2</td>
</tr>
<tr>
<td>Storage contamination risks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1174</td>
<td>3</td>
</tr>
<tr>
<td>Power failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0830</td>
<td>4</td>
</tr>
<tr>
<td>F</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Increase in freight charges</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.3561</td>
<td>1</td>
</tr>
<tr>
<td>Fluctuation in the foreign exchange rates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.2117</td>
<td>3</td>
</tr>
<tr>
<td>Financial risks</td>
<td>0.1635</td>
<td>0.3270</td>
<td>0.1477</td>
<td>0.1635</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub risks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank interest rate fluctuation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.3217</td>
<td>2</td>
</tr>
<tr>
<td>Financial restriction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1105</td>
<td>4</td>
</tr>
<tr>
<td>Demand forecasting errors</td>
<td></td>
<td></td>
<td></td>
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<td>0.4883</td>
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</tr>
<tr>
<td>Uncertainty in market</td>
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<td>0.2142</td>
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<tr>
<td>Bullwhip effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1040</td>
<td>4</td>
</tr>
<tr>
<td>Competitive risks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.1935</td>
<td>3</td>
</tr>
</tbody>
</table>

Table VI. Pair wise comparison relation matrix for main PSC risks

Table VII. Weights and ranking of main risks and sub risks in PSC
the performance. The highest priority stands for machine, equipment or facility failure. Smooth operations ensure the profitability of pharmaceutical industry. Quality risk gets the second position. Quality is an important issue for pharmaceutical products as it is directly related to human life. Other risks like storage contamination risk, power failure gets the third and fourth position in their priority ranking. These two risks can reduce the supply chain performance so it is not negligible during supply chain risk management.

Financial-related risk obtains third position in priority rank and plays a vital role in adopting proactive action against PSC risk. Decision makers should be aware about financial risk and must keep multiple options to recover such risks. In this main risk, there are four risks such as increase in freight charges, fluctuation in the foreign exchange rates, bank interest rate fluctuation and financial restriction. Increase in freight charges gets the first position. The increase in government taxes can raise the cost of production by adding to the cost of supplier’s raw materials and finished goods. Next, bank interest rate fluctuation gets the second position. Managers should conscious about this issue because it may affect the supply chain performance as well as hamper the regular business activity of pharmaceutical companies. The risk dynamic foreign exchange rates hold the third position. Fluctuation in the foreign exchange rates is always unanticipated to predict the conditions. It is indicated as an important risk in pharmaceutical company due to unpredictable exchange rates. It is not predictable that the new business or the new products will be profitable or not (Rao and Holt, 2005; Tang, 2006); thus, manager needs to address this risk effectively. Financial restriction gets the fourth position. Decision makers should give priority to this risk because poor financial plan can hamper the efficiency of supply chain network.

Demand-related risk obtains the last rank in the priority ranking. Variations in demand of pharmaceutical products can affect the business. In this, four risks are involved – demand forecasting errors, uncertainty in market, bullwhip effects and competitive risks. Demand forecasting errors take the first place in ranking. Demand forecasting is one of the important issues for any kinds of business. Forecasting errors can aggravate the demand unpredictability. Thus, top management should conscious about this risk. Increase in demand of supplies, bullwhip effects and competitive risks take the second, fourth and third rank in priority ranking. Due to the rapid increase of pharmaceutical companies in the country, the demand for common supplies is getting higher. Therefore, increase in demand of supplies risk is taking importance in priority risk. The bullwhip effect can be clarified as an event identified by the supply chain network where orders sent to the manufacturer and supplier make larger change than the sales to the end customer (Chen et al., 2000; Geary et al., 2006; Hussain and Drake, 2011). Bullwhip effects indicate demand information distortion within the supply chain. It creates difficulty for the companies to estimate accurate products demand and results in decrease operational performance. Pharmaceutical industries are facing high supply chain risks due to exceptional competition in the local and international market of their products. In this manner, competitor approach and strategy make the new products more uncertain in the market. In Bangladesh, there are lots of pharmaceutical companies present in market, which create more competition among them. This competition may bring market failure or quality failure (Mangla et al., 2015a) of pharmaceutical products.

6. Sensitivity analysis
In this research, among four main risks, supply-related risk holds the utmost priority weight. Moreover, multi criteria decision analysis method cannot deal perfectly to prioritize risk due to human judgment. Mangla et al. (2015a) proposed that small change in relative weights of risks may show the large change in final ranking. Therefore, it is necessary to investigate the ranking for stability of result (Chang et al., 2007). A sensitivity analysis was performed by changing weight from 0.1 to 0.9 with 0.1 as incremental value to supply-related risk to examine the changes in ranking of supply chain risks. At the same
time, corresponding changes in the weights of other risks are also examined. Sensitivity analysis results show that maximum change occurred in the operational risks (O) weights (see Table VIII).

Due to changes in main risks weights, sub risks weights and their ranking are also changed. In this study, at 0.1 value of supply-related risk, specific risk O1 takes the top rank whereas S2, S3, S4 take the lowest rank. Risk O1 holds the highest rank until the value 0.3 of supply-related risk. From value 0.2 to 0.9, the lowest rank was obtained by risk D3. From varying supply risk weights values (from 0.4 to 0.9), the sub risk S1 obtained the top rank whereas O1 hold the second rank for the weights (0.4 and 0.5) and after that S4 takes second rank up to 0.9 weights. At the same time, ranking of other risk was also investigated. Global weights of sub risks when “Supply-Related Risk” value increased from 0.1 to 0.9 are provided in Table IX.

Ranking for sub risks by sensitivity analysis when “supply-related risk” value increases from 0.1 to 0.9 is shown in Table X.

Graphical illustrations for global weights of sub risks and priority ranking for sub risks based on sensitivity analysis are shown in Figures 3 and 4.

At the end, it can be stated that supply-related risk is more important than other risks. Thus, minimizing supply chain risk is significant for managers to improve the effectiveness of PSCs.

7. Managerial and practical implications
The major contribution of this work is the identification and prioritization of PSC risk, which are significant to mitigate the risks as well as to improve overall performance. After realizing basic knowledge on the relevant supply chain risks and vulnerabilities, the industrial manager will be able to minimize supply chain risks by taking proactive policies in the PSCs sector. This study will assists decision makers to identify the most important risks and to suggest means to minimize the risks in PSCs. Some of the policies are also recommended for helping managers in reducing the occurrence of the risks in PSC in Bangladesh, given as below:

- Realizing the actual nature of risk is a pre-requisite to mitigate the risk. This research can be useful to managers for introducing risk mitigation strategies. The managers should set some proactive and reactive strategy to overcome the supply-related risk, which has received the highest weight in the priority rank.

- Managers in the pharmaceutical sectors must develop resilience capabilities to improve PSC system performance and effectiveness. They need a proper understanding of the existing supply chain risks in the first place to develop resilience capabilities of their supply chains. This research can guide them in formulating decision strategies. As quality of pharmaceutical products are vital to human lives, and compromising quality can cause severe reputational and financial loss to pharmaceutical companies. Therefore, operational risks should take into consideration to overcome the quality defects of pharmaceutical products.

<table>
<thead>
<tr>
<th>Main risks</th>
<th>Priority weights for main risks</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>0.3618 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9</td>
</tr>
<tr>
<td>O</td>
<td>0.3270 0.4611 0.4099 0.3587 0.3074 0.2562 0.2049 0.1537 0.1025 0.0512</td>
</tr>
<tr>
<td>F</td>
<td>0.1635 0.2306 0.2050 0.1793 0.1537 0.1281 0.1025 0.0769 0.0512 0.0256</td>
</tr>
<tr>
<td>D</td>
<td>0.1477 0.2083 0.1851 0.162 0.1389 0.1157 0.0926 0.0694 0.0463 0.0232</td>
</tr>
<tr>
<td>Total</td>
<td>1 1 1 1 1 1 1 1 1 1</td>
</tr>
</tbody>
</table>

Table VIII. Main risk values when increasing supply-related risks value from 0.1 to 0.9
Table IX.

Global weights for sub risks when "Supply-Related Risk" value increases from 0.1 to 0.9.

<table>
<thead>
<tr>
<th>Sub risks</th>
<th>Normal</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.1542</td>
<td>0.0426</td>
<td>0.0852</td>
<td>0.1279</td>
<td>0.1705</td>
<td>0.2131</td>
<td>0.2557</td>
<td>0.2984</td>
<td>0.3409</td>
<td>0.3836</td>
</tr>
<tr>
<td>S2</td>
<td>0.0631</td>
<td>0.0174</td>
<td>0.0348</td>
<td>0.0522</td>
<td>0.0696</td>
<td>0.0870</td>
<td>0.1044</td>
<td>0.1218</td>
<td>0.1392</td>
<td>0.1566</td>
</tr>
<tr>
<td>S3</td>
<td>0.0529</td>
<td>0.0146</td>
<td>0.0293</td>
<td>0.0439</td>
<td>0.0585</td>
<td>0.0732</td>
<td>0.0878</td>
<td>0.1024</td>
<td>0.1171</td>
<td>0.1317</td>
</tr>
<tr>
<td>S4</td>
<td>0.0917</td>
<td>0.0254</td>
<td>0.0507</td>
<td>0.0760</td>
<td>0.1014</td>
<td>0.1267</td>
<td>0.1521</td>
<td>0.1774</td>
<td>0.2028</td>
<td>0.2281</td>
</tr>
<tr>
<td>O1</td>
<td>0.1689</td>
<td>0.2382</td>
<td>0.2118</td>
<td>0.1853</td>
<td>0.1588</td>
<td>0.1324</td>
<td>0.1059</td>
<td>0.0794</td>
<td>0.0530</td>
<td>0.0265</td>
</tr>
<tr>
<td>O2</td>
<td>0.0925</td>
<td>0.1305</td>
<td>0.1160</td>
<td>0.1015</td>
<td>0.0870</td>
<td>0.0725</td>
<td>0.0580</td>
<td>0.0435</td>
<td>0.0290</td>
<td>0.0145</td>
</tr>
<tr>
<td>O3</td>
<td>0.0384</td>
<td>0.0541</td>
<td>0.0481</td>
<td>0.0421</td>
<td>0.0361</td>
<td>0.0301</td>
<td>0.0241</td>
<td>0.0180</td>
<td>0.0120</td>
<td>0.0060</td>
</tr>
<tr>
<td>O4</td>
<td>0.0271</td>
<td>0.0383</td>
<td>0.0340</td>
<td>0.0298</td>
<td>0.0255</td>
<td>0.0213</td>
<td>0.0170</td>
<td>0.0128</td>
<td>0.0085</td>
<td>0.0043</td>
</tr>
<tr>
<td>F1</td>
<td>0.0582</td>
<td>0.0821</td>
<td>0.0730</td>
<td>0.0638</td>
<td>0.0547</td>
<td>0.0456</td>
<td>0.0365</td>
<td>0.0274</td>
<td>0.0182</td>
<td>0.0091</td>
</tr>
<tr>
<td>F2</td>
<td>0.0346</td>
<td>0.0488</td>
<td>0.0434</td>
<td>0.0380</td>
<td>0.0325</td>
<td>0.0271</td>
<td>0.0217</td>
<td>0.0163</td>
<td>0.0108</td>
<td>0.0054</td>
</tr>
<tr>
<td>F3</td>
<td>0.0526</td>
<td>0.0742</td>
<td>0.0660</td>
<td>0.0577</td>
<td>0.0495</td>
<td>0.0412</td>
<td>0.0330</td>
<td>0.0247</td>
<td>0.0165</td>
<td>0.0082</td>
</tr>
<tr>
<td>F4</td>
<td>0.0181</td>
<td>0.0255</td>
<td>0.0227</td>
<td>0.0198</td>
<td>0.0170</td>
<td>0.0141</td>
<td>0.0113</td>
<td>0.0085</td>
<td>0.0057</td>
<td>0.0028</td>
</tr>
<tr>
<td>D1</td>
<td>0.0721</td>
<td>0.1017</td>
<td>0.0904</td>
<td>0.0791</td>
<td>0.0678</td>
<td>0.0565</td>
<td>0.0452</td>
<td>0.0339</td>
<td>0.0226</td>
<td>0.0133</td>
</tr>
<tr>
<td>D2</td>
<td>0.0316</td>
<td>0.0446</td>
<td>0.0396</td>
<td>0.0347</td>
<td>0.0298</td>
<td>0.0248</td>
<td>0.0198</td>
<td>0.0149</td>
<td>0.0099</td>
<td>0.0050</td>
</tr>
<tr>
<td>D3</td>
<td>0.0154</td>
<td>0.0217</td>
<td>0.0192</td>
<td>0.0168</td>
<td>0.0144</td>
<td>0.0120</td>
<td>0.0096</td>
<td>0.0072</td>
<td>0.0048</td>
<td>0.0024</td>
</tr>
<tr>
<td>D4</td>
<td>0.0286</td>
<td>0.0403</td>
<td>0.0358</td>
<td>0.0314</td>
<td>0.0269</td>
<td>0.0224</td>
<td>0.0179</td>
<td>0.0134</td>
<td>0.0099</td>
<td>0.0045</td>
</tr>
<tr>
<td>Total</td>
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<td>1</td>
</tr>
</tbody>
</table>
Decision makers should develop sound operational procedures as well as enhance operational and infrastructure resilience to mitigate operational risks. PSC managers must monitor every activity in the supply chain to ensure quality of pharmaceutical products.
Since the supply chain depends majorly on the production of the commodities, to maintain the proper flow of it, it is to be made sure that the production process faces no disruption. The interruption in production affects the entire PSC. In this sense, failure of machines/equipment should be reduced. The machineries involved in production are required to function without error for increasing PSC effectiveness.

As the pharmaceutical sector involves some degree of emergency or essentiality than any other industry, therefore, supplying of necessary materials related to pharmaceuticals should be efficient. This will make sure the delivery of necessary medical service to the society.

From a managerial context, proper storage and handling is suggested in pharmaceutical materials to minimize loss due to expiry of the purchased or produced materials.

8. Conclusions and recommendations for future research

Supply of medicine is a significant priority as a strategic product in any healthcare system. Pharmaceutical organizations, a significant player of the medicine supply chain, are subjected to multiple risks. Therefore, it is necessary to examine the risks to take proactive action for their mitigation. This study proposes an AHP-based model for evaluating the risks in the PSC context. This work is one of the initial contributions in the literature that focused on identifying and evaluating PSC risks in the context of Bangladesh. The 4 most relevant main risks and 16 sub risks were identified through the existing literature review and expert’s feedback through Delphi analysis. The AHP was used to prioritize these risks for determining their priority. Results show that the priority of main risks is as follows: supply risks > organizational risks > financial risks > demand risks. According to the findings, the “supply-related risks” carries the top rank. Therefore, it requires significant managerial attention in increasing PSC effectiveness. The results obtained from this present study may assist to other developing countries to analyze the probable risks in PSC. This work is significant for pharmaceutical industries to deal with their specific vulnerabilities and obstacles faced in their respective supply chains.

This research also carries some limitations. In this study, only 4 main risks and 16 sub risks relevant to PSCs are taken into considered. The identification of the risks may be challenging in any case. Further, Delphi–AHP-based model depends on expert feedback, which may be biased. In the future work, a fuzzy-based AHP tool might be used to avoid the human bias. Also, the proposed Delphi–AHP-based model can be applied in different industry like construction, manufacturing, service, etc., for evaluating the risks, however expert’s feedback may vary with industry. Further, the causal relations may be identified between listed risks in future studies.

References


<table>
<thead>
<tr>
<th>IMDS 118,7</th>
</tr>
</thead>
</table>


Further reading


Appendix 1

Questionnaires survey covering the process of data collection

Phase 1, Identification of most relevant PSC risks in context of Bangladesh

Q.1 What is your designation and experience/role in pharmaceutical industry?

Q.2 Are the listed risks relevant to PSC?

Please write Yes if you think the mentioned risk is relevant to PSC, otherwise write No. You are also free to add/delete any of the risks mentioned in the list.
Phase 2, prioritizing the identified risks with the help of expert’s inputs.

Q.3 Are you realize the assessment scale which we provided to assess the selected risks?

Q.4 Please fill the following comparison matrices using above mentioned scale.

In the same way, please also fill the pair wise relation matrix for the sub risks.
## Table AV.
Main risks and Sub risks in PSC along with their sources

<table>
<thead>
<tr>
<th>Main risks</th>
<th>Sub risks</th>
<th>Simplified meanings</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply-related risks (S)</td>
<td>Fluctuation in imports arrival (S1)</td>
<td>The imported raw materials of the medical products are subjected to various fluctuations, which includes delay in the arrival of the shipping, delay in customs/movement of freights. This will affect the overall efficiency of PSC in turn</td>
<td>Amin (2015), Mokrini, Dafaoui, Berrado and El Mhamedi (2016)</td>
</tr>
<tr>
<td></td>
<td>Lack of information sharing (S2)</td>
<td>Information is the foremost requirement for doing any activity.</td>
<td>Jaberidoost et al. (2013), Yousefi and Alibabaei (2015)</td>
</tr>
<tr>
<td></td>
<td>Key supplier failure (S3)</td>
<td>Failure of any key supplier will disturb the functioning of a PSC in an organizational context</td>
<td>Zsidisin et al. (2004), Blackhurst et al. (2008), Wagner et al. (2009)</td>
</tr>
<tr>
<td></td>
<td>Non-availability of materials (S4)</td>
<td>Sudden disruption may bring non-availability in supply of raw materials. This may add to the disturbances to production function in PSC context</td>
<td>Breen (2008), Mahendran et al. (2011), Ketkar and Vaidya (2012)</td>
</tr>
<tr>
<td>Operational-related risk (O)</td>
<td>Machine, equipment or facility failure (O1)</td>
<td>Failure of any machines/equipment/facility leads to disruptions in the manufacturing process of pharmaceutical products</td>
<td>Mahendran et al. (2011), Finch (2004)</td>
</tr>
<tr>
<td></td>
<td>Quality risk (O2)</td>
<td>Lack of quality products can threaten human life in case of pharmaceutical products. It is important to produce the pharmaceutical products with highest quality as their tendencies to directly affect the health of the patient</td>
<td>Mahendran et al. (2011), O’Connor et al. (2016)</td>
</tr>
<tr>
<td></td>
<td>Storage contamination risks (O3)</td>
<td>Industries are facing issues related to storage contamination during storage of raw materials and finished goods, as pharmaceutical products needs to be maintained at prescribed conditions, such as specified temperature and humidity</td>
<td>Mahendran et al. (2011), Brettler (2015)</td>
</tr>
<tr>
<td></td>
<td>Power failure (O4)</td>
<td>Power failure is a common problem in developing economies, like Bangladesh. Power failures will disturb the production activity and hence lower the overall efficiency of PSC</td>
<td>Finch (2004).</td>
</tr>
<tr>
<td>Financial-related risks (F)</td>
<td>Increase in freight charges (F1)</td>
<td>From a pharmaceutical organizational context, increase in freight charges will have a significant impact on profit margins. The freight charges</td>
<td>Goff (2012)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Main risks</th>
<th>Sub risks</th>
<th>Simplified meanings</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic foreign exchange rates (F2)</td>
<td>Fluctuation in the foreign exchange rates can affect in profit margin of the pharmaceutical products. This risk is unpredictable.</td>
<td>Blome and Schoenherr (2011), Torabi et al. (2016)</td>
<td></td>
</tr>
<tr>
<td>Bank interest rate fluctuation (F3)</td>
<td>Bank interest rate fluctuations may affect the PSC performance as well as hamper the regular business activity of pharmaceutical companies</td>
<td>Blackhurst et al. (2008), Blos et al. (2009), Tummala and Schoenherr (2011)</td>
<td></td>
</tr>
<tr>
<td>Financial restriction (F4)</td>
<td>Poor financial plans and/or financial restrictions can hamper the smooth functioning of PSC</td>
<td>Mangla et al. (2015a)</td>
<td></td>
</tr>
<tr>
<td>Demand-related risk (D)</td>
<td>Demand forecasting errors (D1)</td>
<td>Inaccurate demand forecasts will result in poor supply chain planning and may even create in gap demand and supply of products in a PSC context</td>
<td>Breen (2008), Candan et al. (2014)</td>
</tr>
<tr>
<td>Uncertainty in market (D2)</td>
<td>The demand for common supplies is getting uncertain in market, thus, it is becoming difficult to achieve in a PSC context</td>
<td>Enyinda et al. (2009), Mahendran et al. (2011)</td>
<td></td>
</tr>
<tr>
<td>Bullwhip effects (D3)</td>
<td>The bullwhip effect makes hard for pharmaceutical companies to anticipate exact demand, which may reduce the business performance</td>
<td>Metters (1997), Craighead et al. (2007)</td>
<td></td>
</tr>
<tr>
<td>Competitive risks (D4)</td>
<td>There is a tremendous competition in the local and international market of pharmaceutical products. Thus, pharmaceutical industries are under huge risks due to competitor approach and strategy in introducing new products with improved performance levels</td>
<td>Mangla et al. (2015a)</td>
<td></td>
</tr>
</tbody>
</table>

Table AV.
Appendix 3
Pair wise comparison relation matrices for sub risks under each main risk

<table>
<thead>
<tr>
<th>Risks</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>Relative weight</th>
<th>Rank</th>
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</thead>
<tbody>
<tr>
<td>S1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>0.4262</td>
<td>1</td>
</tr>
<tr>
<td>S2</td>
<td>1/3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.1740</td>
<td>3</td>
</tr>
<tr>
<td>S3</td>
<td>1/2</td>
<td>1</td>
<td>1</td>
<td>1/3</td>
<td>0.1463</td>
<td>4</td>
</tr>
<tr>
<td>S4</td>
<td>1/2</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>0.2534</td>
<td>2</td>
</tr>
</tbody>
</table>

Notes: Maximum eigen value = 4.1610; C.I. = 0.0537

Table AVI.
Pair wise comparison relation matrix for supply-related risks in the PSC

<table>
<thead>
<tr>
<th>Risks</th>
<th>O1</th>
<th>O2</th>
<th>O3</th>
<th>O4</th>
<th>Relative weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>O1</td>
<td>1</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td>0.5166</td>
<td>1</td>
</tr>
<tr>
<td>O2</td>
<td>1/2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>0.2830</td>
<td>2</td>
</tr>
<tr>
<td>O3</td>
<td>1/5</td>
<td>1/3</td>
<td>1</td>
<td>2</td>
<td>0.1174</td>
<td>3</td>
</tr>
<tr>
<td>O4</td>
<td>1/5</td>
<td>1/3</td>
<td>1/2</td>
<td>1</td>
<td>0.0830</td>
<td>4</td>
</tr>
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</table>

Notes: Maximum eigen value = 4.0476; C.I. = 0.0158

Table AVII.
Pair wise comparison matrix for operational risks in PSC

<table>
<thead>
<tr>
<th>Risks</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>Relative weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
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<td>2</td>
<td>1</td>
<td>3</td>
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<td>1</td>
</tr>
<tr>
<td>F2</td>
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<td>1/2</td>
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<td>3</td>
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<tr>
<td>F3</td>
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<td>2</td>
<td>1</td>
<td>2</td>
<td>0.322</td>
<td>2</td>
</tr>
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<td>1/3</td>
<td>1/2</td>
<td>1</td>
<td>0.110</td>
<td>4</td>
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</tbody>
</table>

Notes: Maximum eigen value = 4.0974; C.I. = 0.0325

Table AVIII.
Pair wise comparison matrix for financial risks in pharmaceutical supply chain

<table>
<thead>
<tr>
<th>Risks</th>
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<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>Relative weight</th>
<th>Rank</th>
</tr>
</thead>
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<td>D2</td>
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</tr>
</tbody>
</table>

Notes: Maximum eigen value = 4.1193; C.I. = 0.0398

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Managing supply chain risks and delays in construction project

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Abstract
Purpose – The purpose of this paper is to investigate models and methods for managing supply chain risks and delays in construction projects.
Design/methodology/approach – The study mainly employs quantitative analysis in order to identify disruptions in construction supply chains. It also uses paradigms of simulation modeling, which are suitable for risk assessment and management. Both qualitative and quantitative data were collected through a literature review and details of specific construction projects, respectively. A dynamic modeling method was used, and the model was provided with an event-based simulation. Simulation modeling was used to measure the performance of the system.
Findings – The study shows the benefits of applying the dynamic modeling method to a construction project. Using event-based simulation, it was found that construction delays influence both the magnitude and the probability of disruption. This method contributes to the existing theoretical foundations of risk management practices, since it also considers the time factor. This method supplements the Monte Carlo statistical simulation method, which has no time representation. Using empirical analysis, the study proposes increasing the safety stock of construction materials at the distribution center, so as to mitigate risks in the construction supply chain.
Research limitations/implications – The research considers a single case of a hypothetical construction project. The simulation models represent a simple supply chain with only one supplier. The calculations are based on the current economic scenario, which will of course change over time.
Practical implications – The outcomes of the study show that the introduction of a safety stock of construction materials at the distribution center can prevent supply chain disruption. Since the consideration of risks at all stages of construction supply chain is essential to investors, entrepreneurs and regulatory bodies, the adoption of new approaches for their management during strategic planning of the investment projects is essential.
Originality/value – This dynamic modeling method is used in combination with the Monte Carlo simulation, thus, providing an explicit cause-and-effect dependency over time, as well as a distributed value of outcomes.
Keywords Risk management, Construction projects, Construction delays, Simulation modelling
Paper type Research paper

1. Introduction
Construction projects are inevitably related to a future period of time so that it is problematic to predict the results of their implementation. They depend on how accurately the amount of material and their associated flows during the project are forecasted. Insufficient information is a problem, and stochastic materials flow through the value stream likewise hinder the universal application of lean principles to the construction supply chain (Fearne and Fowler, 2006; Forsman et al., 2012; Eriksson, 2010). In essence, the lean concept focuses substantially on the process flow, and a synchronization of
demand and production. Therefore, it is difficult to implement this in the construction industry, due to its inherent uncertainty and complexity, both of which cause disintegration in its supply chains (Voordijk et al., 2006; Briscoe and Dainty, 2005; Fearne and Fowler, 2006). Hence, the construction supply chain should be developed within the framework of the “agile paradigm” (Vrijhoef and Koskela, 2000). Nevertheless, this study supports the idea of using a material inventory to avoid supply chain disruption in the construction industry.

Difficulties in planning construction projects result in the work flow variability causing inefficiency in downstream processes that result in delays and the associated costs. Accordingly, it is crucial to consider all possible outcomes and the influence of risk factors due to disruptions in the construction supply chain. Risk factors affect the value of investment in construction projects, by inducing a deviation of future cash flows from the expected flow within the project, which results in firms exceeding their budget goals. For so-called “megaprojects”, risks may result in cost overruns during the process of their implementation with more than 100 percent overspending from the expected budget appraisals, and the incurring of additional costs even before the construction begins.

The actual financial cost of the longest underwater railway, the Channel Tunnel, was sharp 140 percent higher than the estimated investment cost (Flyvbjerg et al., 2003). The increase in cost by 55 percent of the Great Belt Bridge (Denmark) was noted three years before the expected date of completion of the project, while the change in the cost (+10 percent) of the Öresund Bridge (Sweden) was recorded even before the start of its construction (Bruzelius et al., 2002). The underestimation of risk factors for projects, especially capital-intensive ones, at the stage of their feasibility study, leads not only to unexpected financial losses, but also delays in projects commissioning. However, the number of studies that address the delays and cost overrun issues simultaneously in construction projects is not sufficient. Previous studies focus on the delays alone and not on cost overruns or both (Ramanathan et al., 2012).

A risk-free asset is a case of hypothetical construction, which is widely used in the theory of finance, however, in the real life is impractical to achieve (Black et al., 2012; Shapkin and Shapkin, 2013). It is essential to restrain the previously mentioned types of risk, which have numerous causes, primarily construction delays (Ramanathan et al., 2012). Some authors note that the cause of these risks is rooted in close deadlines due to changes in construction schedules, incorrect forecasts of traffic volumes, an easing of bidding rules and possibly corruption as well. Other authors emphasize that failure factors are rooted in inaccurate data and irrational research methods (Panova and Hilmola, 2016; Bruzelius et al., 2002; Flyvbjerg et al., 2003). From this point of view, the development of methods and models that consider and assess construction risks in terms of their initial cost estimate is a fundamental task from both a practical and theoretical points of view.

The probabilistic nature of risks is difficult to consider on the basis of analytical formulae. The inappropriateness of some methods for assessing the investment in infrastructure projects has led to a combination of different methods (e.g. deterministic and stochastic approaches using the Monte Carlo analysis (MCA); Esipova et al., 2010; Salling, 2013; Lorenzo et al., 2012; Ambrasaitė et al., 2011). The Monte Carlo test is one of the most suitable methods of quantitative risk assessment, since it can deal with the greatest possible number of risk factors (Panova and Hilmola, 2016). However, the method has no explicit time representation and aims to solve the deterministic problem probabilistically. Therefore, in order to describe the dynamic system, which is represented by the construction project, the application of dynamic modeling is proposed. In particular, by means of an event-based simulation of construction delay issues, the magnitude and the probability of the disruption can all be explained explicitly.
The aim of this research is to investigate models and methods for managing supply chain risks and delays in construction projects. The specific research questions are:

* **RQ1.** What models and methods are suitable for the economic appraisal of construction project delays?

* **RQ2.** How can construction delays regarding time and cost risks be assessed and mitigated by a combination of different methods?

Both qualitative and quantitative methods were used to address these questions. The qualitative data were collected through a literature review, in order to explore various possible disruptions in construction supply chains, and to identify simulation modeling and risk assessment methods. The quantitative data were collected through the detailed hypothetical construction project and was subjected to simulation modeling techniques.

The remainder of this paper is structured as follows. To begin with, an overview of relevant models and modeling methods and specifically those for managing delays in construction projects is provided in Section 2. The research method for this research is then described in more detail in Section 3. Thereafter, the simulation models and their outcome are discussed in Section 4. Finally, the research is concluded and venues for further research are proposed in Section 5.

2. **Models and methods for managing construction delays**

2.1 **Lean concept in construction supply chains**

The lean concept has been widely applied in manufacturing to reduce waste that restricts process efficiency. However, the development of production processes by adopting lean principles in the construction supply chains is still in its infancy (Forsman et al., 2012). The peculiarities of this industry prevent the elimination of all waste in its supply chain.

Out of the seven wastes in the lean concept (Forsman et al., 2012); inventory waste is hardly eliminated at all from the construction supply chain. In many instances, inventory is essential for companies, because of imbalanced demand and production capabilities, long distances between suppliers and customers, low delivery reliability and speculative intentions as well as inflation expectations (Lukinskiy and Panova, 2017).

Unlike other supply chains, for example, vehicle manufacturing or retail distribution industrial sectors, which are highly integrated, the realization of truly integrated construction supply chains is problematic and difficult to achieve (Briscoe and Dainty, 2005). Therefore, lean principles cannot be fully applied. Many authors stress that in construction sector, fragmented integration stems from supply chain complexity (Voordijk et al., 2006; Briscoe and Dainty, 2005; Fearne and Fowler, 2006). In particular, Voordijk et al. (2006) provide multiple case study evidence on the modularity of construction supply chain, that it exhibits low proximity and being represented by geographically dispersed actors, is characterized by autonomous managerial and ownership structures, diverse cultures and low electronic connectivity (in contrast to supply chains in other sectors which have a high degree of integrality).

Briscoe and Dainty (2005) also stress the existence of various different companies supplying materials, components and a wide range of construction services, as well as a large subcontracted workforce, which limit opportunities for process integration. Moreover, the construction projects themselves are treated as a series of sequential and predominantly separate operations, for which the individual participants are not particularly committed to the common goals, e.g., long-term success of the final construction (Briscoe and Dainty, 2005; Fearne and Fowler, 2006).

Of critical importance is uncertainty, a characteristic of most construction projects (Fearne and Fowler, 2006; Oparin, 2015; Flyvbjerg et al., 2003; Bruzelius et al., 2002). In order
to respond to this feature, responsibility and flexibility are essential. For this reason, construction supply chains should be developed within the framework of the agile paradigm, rather than that of lean thinking (Vrijhoef and Koskela, 2000). Even though lean thinking reduces variability and buffer stocks, which make the supply chain efficient, it is stripped off its capacity to respond to adverse specifications and to change in the operating environment (Fearne and Fowler, 2006). In fact, authors underline that the ubiquitous and indiscriminate usage of lean thinking may result in sub-optimization or so-called local efficiency (Fearne and Fowler, 2006; Forsman et al., 2012) that can reduce the project’s overall effectiveness.

Adoption of the lean concept is limited and depends on the extent to which it is really required. For example, Eriksson (2010) found that lean-related aspects have been broadly utilized in projects, when they focus on cooperation and serve as the starting point for a fully-fledged utilization of the lean concept. Thus, informal collaborative efforts have been used explicitly as an aspect of the lean concept in the specific case (Eriksson, 2010; Khalfan et al., 2007).

Meanwhile, other aspects of the lean concept, like just-in-time (JIT) deliveries, and joint IT tools that relate to waste reduction, were as above only implicitly used to some extent (Eriksson, 2010). This favors the idea that the complete elimination of inventory, supported by JIT operations, are difficult to achieve in the construction sector. Many authors point out the slow growth in efficiency of construction industry, compared to the aerospace and automotive industries where the productivity improved substantially during the last few years (van Lith et al., 2015; Tookey et al., 2005).

Therefore, substantial research has been done to solve the problems that arise in construction supply chains. Considering the above difficulties in planning construction projects, this study addresses the formal methods and models of the construction supply chain management.

2.2 Models for estimation of construction delays

Ameyaw and Chan (2013) present a comprehensive analysis of risks related to specific infrastructure projects including transportation, telecommunications, power and energy plants. The breakdown of risks includes 81 factors. Based on the varied classification of risks, it was found that the most frequent ones were political, construction and operational, including land acquisition and financial/market risks. The review study of Ramanathan et al. (2012) identified 113 factors responsible for delays, which were classified into 18 groups.

According to Ramanathan et al. (2012), the groups responsible for the success of project realization have been ranked as: Owner (Rank 1), Contractor (Rank 2). In this regard, it is necessary to take into account the assessment and mitigation of risks related to the contractor (e.g., delays in assets transfer, material supply delay and of other resources; timeliness of loading and shipment of goods during the transportation stage).

Beyond the identification of causes and disruptions in construction supply chains, it is important to evaluate the associated risks, since they affect the estimated return on investment of the project. The concept of risk is also linked to uncertainties associated with events. In the context of construction projects, risk is commonly associated with an uncertain event or a condition that leads to a positive or a negative outcome with respect to the project’s objectives. The concepts of risk and uncertainty in the literature are not always identical. Uncertainty is the incompleteness and inaccuracy of information about the conditions of project implementation (Oparin, 2015). Authors in the area stress that risk is the possibility of occurrence during the project implementation, of conditions, which will or may lead to negative consequences for all or individual project participants. When there is a risk, each alternative generates a probability distribution over possible consequences, and the decision-maker has to choose on the basis of this probability of
distributions (Black et al., 2012). If the probability is unknown, then the choice is made under uncertainty, which is the perceived inability to make accurate predictions and calculations (Milliken, 1987; Knight, 2012).

In this paper, the realization of an investment project for a container terminal which undergoes the delay of material supply to the construction site, and as a result, the overall delay in commissioning phase is being analyzed. Accordingly, the assessment of the construction risks is considered as a prerequisite for their mitigation. For the estimation of those risks, one of the most important capital-budgeting models is applied, for example, net present value (NPV) and discounted payback period (DPP). The statistical mean of the NPV and DPP is used to determine the expected cumulative profit and payback time for the investment respectively, while the standard deviation determines the risk, with respect to the budget and timing of the construction project.

Two capital-budgeting models are proposed because NPV, first, is perceived as a superior technique (Keown et al., 2003; Dymowa, 2011; Pyles, 2014), despite the fact that economic appraisal of construction projects relies on a stream of capital-budgeting techniques such as payback period, profitability index, internal rate on return, modified internal rate of return and DPP. Also, NPV can recognize the time value of money, which differs from the payback period (Pyles, 2014).

Second, the use of the payback period as a decision-making criterion has its own benefits, such as that it is easy to visualize, is understandable, easy to calculate and can indicate the projects’ liquidity (Keown et al., 2003). Moreover, the DPP can be adjusted for the time value of money. Bhandari considers six capital budgeting decision criteria, of which the discounted payback satisfies ten characteristics (e.g. simple to understand, measures profitability, ensures liquidity, etc.). None of the six criteria meet all the requirements of an ideal criterion like DPP and NPV.

It should be noted that the NPV rule ensures profitability, but not liquidity. In other words, decision-making on the acceptance of the project on the basis of a positive NPV does not take into account the time period, or a project’s useful life that is exposed to risks, due to the disruption in construction supply chain. These peculiarities can be easily indicated with the use of DPP. For this reason, the DPP is not a less important criterion than NPV, and is more effective for use as a decision-making technique for construction delays in the investment projects. Its benefits are indicated through its application in economically assessing the construction project (container terminal). The benefits of both analytical models, such as NPV and DPP, for the assessments of delays of infrastructure projects, can amplify if these models are be calculated by using simulation platforms (e.g. Panova and Hilmola, 2016).

2.3 Qualitative and quantitative methods for risks assessment

There are various methods for assessing the probability of failure, and risks on the performance criteria, e.g., based on expert estimations, method of analogies (qualitative methods), simulation techniques, MCA (quantitative methods) or semi-quantitative approaches.

Risk assessment is a technical and scientific process by means of which the risks of a given situation for a system are modeled and quantified. For the development of a container terminal, risk estimations can facilitate its successful implementation. However, not all assessment methods can be beneficial for construction project delay assessment, due to various shortcomings.

Qualitative risk analysis employs judgment and sometimes expert opinion to evaluate probability and consequence values, while quantitative analysis relies on probabilistic and statistical methods. To increase the reliability of expert estimates, the pairwise comparison method, also known as analytic hierarchy process (AHP) is often used in decision making.
support systems. Dey (2009) identifies construction project risk levels in an AHP framework, while Gaudenzi and Borghesi (2006) apply the method for assessing risk in supply chains. Thus, the AHP supports managers in demonstrating the relationships of the overall goal, as well as supply chain objectives, in identifying risks and assessing their potential impact within the chain.

Apart from expert estimations, no less common in the qualitative assessment of investment risk is the method of analogies or estimation by analogies, EBA, or analogy based estimation. The main difficulty with this method is in achieving the correct selection of the analogy, because there are no formal criteria for establishing the degree of similarity of situations. Decision-makers on less familiar terrain must look to other industries for comparisons. For example, a company shifting from a product-based to a service-based business model might consider IT companies that have already made this shift (Courtney et al., 2013). Consequently, although business leaders frequently use analogies to inform their decisions, many fail to do so in a rigorous, systematic manner (Courtney et al., 2013).

Meanwhile, expert judgments are quite often used to describe risks so that the uncertainties in expert judgment, as well as the resulting variance of the risk calculation cannot be entirely eliminated (Pluessa et al., 2013). In general, qualitative methods offer analysis without detailed information, and the intuitive and subjective process may result in imbalanced outcomes by those who use them. Because qualitative methods do not allow determining the numerical magnitude of the risk associated with the investment project, this can be the basis for further research using quantitative methods.

The latter methods are widely based on the mathematical apparatus of probability theory, that is, mathematical statistics. The main objective of the quantitative approach is to determine the impact of risk factors on efficiency criteria of the investment project. Accordingly, quantitative analysis is more desirable for container terminal project economic assessment, in terms of obtaining accurate results.

The most widely used method in the risk assessment of investment projects (especially productive investment) drew on several quantitative methods, such as that of adjusting the discount rate, sensitivity analysis (method of variation of parameters), scenario method (the method of formalized description uncertainties) and the Monte Carlo method (Popova, 2011).

The use of quantitative methods enables to obtain a numerical estimate of the riskiness of the project, thus determining the degree of influence of risk factors on its effectiveness. In particular, Monte Carlo simulation enables researchers to evaluate the accuracy of the sampling risks (Carlos and Fernández, 2013). In the Monte Carlo simulation method, the computer generates hundreds of possible combinations of parameters (factors) of the project with regard to their probability distributions. Each combination gives a value of the performance criteria, and in the aggregate, the analyst obtains a probability distribution of possible project outcomes.

Thus, MCA is frequently used for calculating the discounted cash flow (DCF) and free cash flow (value-based management models). With the use of MCA, the evaluation value of the DCF approach amplifies, because MCA allows taking into account the probabilistic environment, which increases the accuracy of the DCF approach (Amédée-Manesme et al., 2013). More specifically, Monte Carlo is applied to calculate NVP from a probabilistic perspective (Bannerman, 1993; Amédée-Manesme et al., 2013; Piranfar and Masood, 2012; Samis and Davis, 2014). This research is also geared toward a proliferation of the use MCA for calculating the DPP, in order to assess risks in the container terminal project from the probabilistic perspective.

At the same time, it should be noted that in the statistical simulation method of Monte Carlo, which aims to solve the deterministic problem probabilistically, there is no explicit time representation. Therefore, the list of quantitative methods for risk assessment
(Popova, 2011) can be complemented by the method of dynamic modeling, which takes into account the time factor (Panova and Hilmola, 2016). To describe a dynamic system, which includes the development of an infrastructure project in phases with construction delays, dynamic modeling can be used in combination with the Monte Carlo method. The combination can be enabled by the use of modeling tools. Specifically, to solve the problem, it is preferable to employ the simulation systems described below.

3. Research methodology
This present research describes methods of assessing the risks associated with delays in construction projects through comparative analysis. It also explains the stochastic nature of risk factors in construction projects. A literature review was used to determine the risk factors (e.g. time and cost), as well as approaches for their management. An experimental analysis was used to empirically validate the findings from the literature, conducted using visual simulation modeling experiments with the help of AnyLogic and Vensim computer packages.

3.1 Research strategy
This research employs both qualitative and quantitative methods. The former used is a literature review, in order to explore the various disruptions in construction supply chains. The literature review also enabled collecting background information on the topic. The paper selection was from four databases: EBSCO Business Source Complete, Emerald Insights, ProQuest and E-library (Russian database). Works in English and Russian were included. To ensure research quality, only papers published in peer-reviewed journals were considered.

The quantitative data were gathered from a hypothetical construction project. Dynamic modeling was used, and the model was provided with an event-based simulation. Simulation modeling was used to measure the performance of the system. The complex system was divided into different parts for an experimental analysis. A finite number of parts were identified. The financial flows were divided into revenue, taxes, profit, operational cost, initial investments, etc., as these were convenient to incorporate in the first model. By contrast, in the second model, the system was represented by a finite number of events, such as the generation of demand for materials for a construction project, ordering of materials and update of inventory.

3.2 Data collection
To answer the research questions, both qualitative and quantitative data were used, which led to a better understanding of both the objects and subject of the investigation. The objects are the construction delays and associated risks, which were assessed in the context of the investment project, while the subject(s) are the financial flows affected by risk factors.

An in-depth review of the relevant literature was used to ensure the content validity of the research. The first part of the literature review yielded in the qualitative data from various sources, while the second part of the literature review concerned the quantitative data. This was in addition to the qualitative data, which helped to conduct the feasibility study on risk mitigation, with respect to delays in the delivery of materials to the construction sites (the secondary qualitative data were mainly in the form of analytical formulas).

3.3 Data analysis
Vensim and Anylogic were used as simulation environments for data analysis. The first computer package provides the simulation with the help of a systems dynamics approach.
System dynamics concentrates on dynamic complexity, which is created by multi-loop feedback (Sterman, 2000). In the present study, the relationship in the causal financial diagram is simple, without considering looping, described with the help of Excel. However, this causal financial diagram requires an MCA. In Excel, it is less extended, without a sophisticated graphical representation of the model outcome (unlike the Vensim package, where MCA is built into the program, and can be applied to any model designed there). Moreover, the sensitivity test itself was more important in the current research than the feature of the Vensim environment for building complex models.

Moreover, an area of interest is the analysis of changes which occur during different time periods, also referred to as the scope of dynamic complexity (Hilletofth and Lättilä, 2012; Hilletofth et al., 2009; Hilletofth, Aslam and Hillmola, 2010; Hilletofth, Ujvari, Lattila and Hillmola, 2010). In particular, the Vensim environment was used to explore the simple system in time, under the impact of risk. This system was represented by the financial flows related to the construction project, developed in phases subject to risk. These risks were assessed by the superior capital-budgeting model, NPV.

The Vensim program contains the built-in dynamic function for computing the NPV of the project. This dynamic function of the program returns the NPV of the stream, computed using the discount rate. The computation assumes that the stream is valued at the end of the period and that the discount rate is considered as a discrete period rate. This is the same set of assumptions that Excel uses, although, Vensim allows a simultaneous MCA and representing the results in the form of a sensitivity graph.

Unlike the Vensim program, AnyLogic contains a lesser number of built-in dynamic functions and tools for representing Monte Carlo outcome, despite the fact that systems dynamics models are supported by AnyLogic. This is because Vensim is used specifically for analyzing the systems dynamics of complicated environments (e.g. how corporate produce successes and failures). On the other hand, AnyLogic is suitable not only for the application of systems dynamics, but also for agent and event-based approaches, either separately or in combination within one model. This provides the opportunity for pure coding, as well as a reasonable level of detail and off-the-shelf functionality, which makes Anylogic a good toolset for creating hybrid models (Lättilä et al., 2010; Hilletofth, Ujvari, Lattila and Hillmola, 2010).

In the current study, it would be possible to create a hybrid model, if the AnyLogic software had more extended Monte Carlo analyses (possibility to represent the outcomes in the form of statistics, sensitivity graphs, tables, etc.). However, it would take a long time, since not all of the simulation paradigms are easily matched. For example, SD models are continuous by nature, and have difficulty coping with discrete events (Lättilä et al., 2010). Due to these reasons, the second model was built in Anylogic.

It should be noted that the interaction between different simulation programs was provided manually. For instance, the data outcome was obtained from the Anylogic model, and applied to the model developed in Vensim. In Anylogic, there is a built-in feature for converting the models developed in Vensim, so as to access them in the Anylogic. However, Vensim does not provide such an ability to serve the needs of the current research.

The event-based simulation was applied in order to build the second model with information on construction delays in the supply chain. As the structure of the system tends to be fixed in the system dynamics paradigm, it is easier to use the other paradigm to study systems, which tend to evolve through time (supply networks are a good example; Lättilä et al., 2010). In the built model, the event was the simplest way to plan actions. Overall, events are often used to model delays.

The behavior of the second system was modeled by action charts and three types of event. The first event occurs after the timeout, which was used when there was a need to schedule the execution of some action at a certain point in time. An event type that occurs
after the timeout was used in combination with additional option of the cyclic mode (e.g. for the generating demand for materials at the construction sites). The second event, triggered by timeout, was used in combination with other modes (occurring ones). It was applied for the computation of stockout costs at the end of the simulation period. The third timeout event was complemented by the managed manually mode. It was triggered by the action chat and simulated the completion of a new order of construction materials and simultaneous update of the stock level at the warehouse.

In conclusion, it should be noted that the simulation models were used for explanatory purposes, providing an overall understanding of the system, rather than a normative one. Unlike a normative system, for which simulation models are normally validated with historical data, the other models might yield suggestions that are far from optimal (Lättïä et al., 2010). Thus, the computer simulation merely helped to explain how the construction delays occur and influence the disruption, rather than yield normative results.

4. Findings

4.1 Base scenario of the system dynamics model for financial flow analysis

In order to analyze and assess the risks associated with the project of creating a container terminal, it is necessary initially to calculate, in a risk-free environment, indicators such as income, expenses, gross and net profits, taxes, etc. for the entire period of the project realization (from 2017 to 2022). The calculations mainly employed analytical formulas from Panova and Hilmola (2016). It was assumed that the center is planned to perform logistical services, such as cargo and container handling, warehousing, organization of cargo delivery by trucks, customs clearance, etc. The computation of the financial plan was based on data from the Russian companies providing a similar complexity of logistics services to the project under consideration. For the economic appraisal of the hypothetical container terminal project, which was exposed to various risks, the initial value of capital investments was estimated at approximately 10 ML EUR (Table I).

The income and expenses were associated with by provision of logistics services. Indirect expenses were calculated with allowance for the wages payment fund and administrative costs. For the calculation of the NPV and DPP, the interest rate was taken at 11.8 percent, allowing for the key refinancing rate of 8.5 percent provided by the Central Bank of Russia (since September 18, 2017) and the level of inflation of 3.3 percent (Cbr, 2017). To foresee the growth of income, as well as expenses over the settlement period of six years, a chain price index (also known as consumer price index for the UK and USA; Black et al., 2012) was taken into consideration. It should be noted that the whole financial plan was calculated the investor point of view.

To calculate NPV and DPP in a risk-free environment (so-called base-scenario), the simple model was developed in the Vensim program (Figure 1).

Based on the output of the model, the NPV and DPP were determined. In particular, the accumulated profit equals 7.248 ML EUR, while the investments will pay off in three years and 3.8 months (Figure 2).

4.2 Discrete-event model for the analysis of delays in the supply of materials

For the analysis of construction delays during realization of the project, it was proposed to focus on the risks related to the contractor, particularly untimely delivery of the materials

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<thead>
<tr>
<th>Capital investment</th>
<th>Taxes</th>
<th>Income</th>
<th>Expenses Direct</th>
<th>Indirect</th>
<th>Gross profit</th>
<th>Net profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>10,000,000</td>
<td>125,530</td>
<td>9,480,900</td>
<td>5,266,000</td>
<td>1,185,000</td>
<td>3,029,900</td>
<td>2,904,369</td>
</tr>
</tbody>
</table>

Table I. Financial plan (in EUR)
(e.g. rolled metal products) to the rent warehouse. To estimate the influence of delays, the second model was developed according to discrete-event approach in AnyLogic program (Figure 3).

By using the simulation model, it is possible to analyze how the supplier, whose services the constructor company has been using for a period of one year, influences the activities of the organization. As in the first model, it is necessary to look first at the risk-free scenario (without construction delays). To perform this scenario, the following parameters were formed: per day, from the leased warehouse, eight tons of rolled metal products, with a standard deviation of three tons, are consumed. These parameters can be observed from

![Figure 1. The system dynamics model for appraisal of investment in the container terminal](Image)

<table>
<thead>
<tr>
<th>Date</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>-7.096 M</td>
<td>-3.737 M</td>
<td>-923.500</td>
<td>1.891 M</td>
<td>4.616 M</td>
<td>7.248 M</td>
</tr>
<tr>
<td>DPP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Figure 2. The deterministic output of the model (in ML EUR)](Image)

![Figure 3. The discrete-event model for the assessment of delays in supply of materials](Image)
Figure 3 (“MeanDemand” and “DevDemand”). The daily demand was calculated dynamically via the function of normal distribution over the simulation period of the experiment, which equals 365 days. This figure was represented by the demand parameter. The list of all parameters can be seen on the left of Figure 3 (in the form of gray circles).

Mean lead time for the delivery of materials from the producer is five days (parameter “MeanLeadTime”, which is identical to the “LeadTime” in a risk-free scenario without delays (“DevLeadTime” = 0, Figure 3). In addition to the already defined parameters, other static parameters were introduced to the model: Z value to define the service level of 99.9 percent, which corresponds to 3.08, and “FineforStockOut”, which equals EURO 1,000 and helped to calculate the risk of stockouts in the warehouse. The parameters “SafetyStock”, target inventory and “CurrentInventory” were updated during the experiment with the help of respective events (“OrderingPolicy”, “NewOrder”, described in Section 3.3) and the action chart.

The created events and the action chart were also used for real-time variable changes and for accumulating of the required information during the simulation experiment (e.g. the volume of “Retailshortage”, “TotalFinesforStockOut”, “TotalSales”, which was generated by the daily demand). One variable “OrderReceived” served as the supportive one in the action chart. It had a Boolean value and was used in defining of the replenishment rule at the warehouse. In particular, for the management of inventory at the warehouse, the “Minimum-maximum” policy, with a continuous review of inventory levels (ILs), was employed as the most flexible, in turns of stochastic demand (Lukinskiy et al., 2016, 2017; Lukinskiy and Panova, 2017).

Relying on the more or less timely delivery of materials, the space for storing the rolled metal products at the contractor warehouse was calculated with an allowance for the safety stock levels and re-order point (ROP), defined by the formula (with the demand variable, and the lead time constant; Lukinskiy et al., 2017):

\[
ROP = d \times L + z \times \sigma \times \sqrt{L},
\]

where \(d\) is the average demand, which determines the decrease in the IL, \(L\) the lead time, \(Z\) the number of standard deviations (i.e. the normal distribution parameter, which corresponds to the probability of stockouts, 3.08, corresponds to 99.9 percent service level from the standard normal distribution function), \(\sigma\) the value of the standard deviation of demand during lead time.

The outcome of the model with the parameters that describe the risk-free environment, show that materials are always in stock and inventory is kept at the minimum level (Figure 4(a)).

The second scenario is not free from risks. Delays in the supply of material from the producer were modeled by the parameter (“DevLeadTime”). For this purpose, the input data of the model was corrected (i.e. the value of parameter “DevLeadTime” was set to 3 days instead of 0, as used in the first risk-free experiment). Since the lead time was not constant, the delays caused an IL with stockouts (Figure 4(b)); in the hypothetical model, the ILs were fixed even below the zero line, so as to calculate the total fines related to the cases of stockouts. Specifically, the stockouts resulted in fines that the supplier would pay to the contractor of the project. Each ton of material, which was not delivered on time to the constructor warehouse was estimated at a value of EURO 1,000 (defined by the parameter “FineforStockOut”).

To a greater extent, the stockouts at the warehouse result in delays in constructing the project. In fact, the owner/designer of the project encounters postponements that entail
unproductive hours of both the workforce and equipment, as well as fines due to deviations from the planned period of construction of the container terminal and the corresponding lost income. The lost income per day due to the delay in commissioning the project can be defined from the yearly expected income (Table I).

Payment of forfeit (fines) due to deviation from the planned period of construction is regulated by a special rule of law. The amount of the penalty is calculated as a percentage of the contract price for each day of delay. The interest is calculated as 1/300 of the refinancing rate of the Central Bank of the Russian Federation on the day of fulfillment of the obligation. For example, the conditional refinancing rate on the day of consideration is 8.5 percent, the conditional price of the project: EURO 10,000,000 and the length of the delay is the 1 year (365 days, in the worst-case scenario). The forfeit amount can easily be determined

\[
10,000,000 \times 365 \times 1/300 \times 8.5/100 = 1,034,167 \text{ EUR/year}
\]

The idle time of the workforce was calculated from the assumption that the salary of workers in a month is EURO 60,000, when the salary per day is EURO 2,000 for the workforce. The average number of people in construction brigade is 20. By knowing the delays, it is possible to calculate that the amount of money that the company spends on wages for workers on days of idle time (simply by multiplying those figures). Similarly, the

\[\text{Figure 4. The dynamics of inventory level}\]

\[\text{Notes: (a) Risk free environment; (b) with delays in supply chain}\]
idle time for equipment can be calculated. The work value of the crane per day is estimated at EURO 15,000 and trucks at EURO 8,000. Hence, by multiplying by the number of days of delays, it is possible to calculate the cost to the owner.

In order to calculate the additional financial flows due to the delay of materials delivery from the supplier to the construction sites, it is necessary to determine the number of stockouts at the contractor warehouse. Just one run of the model with constant risk parameters (i.e. deviation in the lead time, which equals to three days) is insufficient. The reason is that during the run of the model, random probability samples were used. Hence, the output from one experiment would be the only individual result of a random variable with a large variance. Therefore, in order to obtain more reliable data on the number of days of stockouts in the warehouse, further 10 runs of the model were provided, in order to find mean values and standard deviations of the considered variable (Table II).

On the basis of ten values obtained from the normal distribution of the random variable, one can find the mean values and define a confidence interval. In particular, the mean value for the days of stockouts is 13, with the standard deviation of three days; thus, at a 95% confidence interval, the limits are [16, 10], and the average stockout volume is 179 with the standard deviation of 54 or [233, 145].

4.3 Adjusted financial model for the assessment of risks related to time and cost

In order to estimate the impacts of the material supply delays on the project, the financial flow model was adjusted (Figure 5). It was assumed that the days of stockout result expenses for the owner, which was discussed in the previous section.

For this reason, additional constant parameters, such as daily expenses, were added to the model. Meanwhile, the days of stockouts were set as a variable with the help of a normal distribution (Table III).

During the Monte Carlo experiment (with 20,000 runs), the delay parameter was varied, while the other parameters were set as constant. The output of the model can be analyzed via the sensitivity graph and generated statistics (Figure 6).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Days of stock outs</td>
<td>22</td>
<td>8</td>
<td>12</td>
<td>16</td>
<td>14</td>
<td>14</td>
<td>8</td>
<td>5</td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>Stock out, tons</td>
<td>304</td>
<td>64</td>
<td>120</td>
<td>226</td>
<td>176</td>
<td>206</td>
<td>134</td>
<td>56</td>
<td>350</td>
<td>156</td>
</tr>
</tbody>
</table>

**Table II.** Output of the experiments, representing delays and stock outs

![Adjusted model of financial flows on the construction project](image-url)
In Figure 6, the sensitivity graph shows various confidence bounds. The Vensim program allows entering up to eight confidence-bound regions (in any order) and the corresponding color that should be used to display them. For example, for a confidence bound at 50, 1/4 of the runs will have a value exceeding than the maximum of the confidence bound, and 1/4 will have a value lower than the minimum. With regard to the sensitivity graph, the investments will pay off over an average time frame of 3 years 8.5 months (DPP). However, the DPP can deviate from the average figure by ±1.3 months with a probability of 75 percent or might be ±2.1 months (with a probability of 95 percent). On the whole, the risks of delays resulted in an increase of the DPP by almost 5 months, compared to the risk-free scenario (3 years and 3.8 months).

The risk of delays also affected the NPV. On average, NPV decreased by 17 percent from the base scenario of the risk-free environment. The mean, minimum and maximum values of NPV were 6.156, 5.406 and 6.828 ML EUR, respectively, with StDev 0.246 ML EUR and a low unitized risk value also known as the coefficient of variation of 4 percent (Figure 6). With respect to the confidence intervals, which were installed during the simulation experiment, and the table of cumulative probability (or table of normal distribution), the following assumptions were made. A rate of 75.18 percent corresponds to a satisfaction level \( Z = 1.15 \). Thus, the probability value of obtaining an NPV, which belongs to the boundaries \([6.156 - 0.246 \times 1.15; 6.156 + 0.246 \times 1.15]\) ML EUR equals 75.18 percent. Since our random variable (NPV) has a normal distribution, it is possible to use the rule of three \( \sigma \) (Figure 6). Following this rule, which states that the probability of a random variable falling within the confidence interval \([M - 3\sigma, M + 3\sigma]\) is close to 1, it is possible to conclude that, with a probability of 99.7 percent, the largest possible amount of losses under the project is EURO 0.739, while, with a probability close to 0, and the NPV of the container terminal project could be below 5.406 ML EUR.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily expenses on brigade of 20 workers</td>
<td>EURO 40,000</td>
</tr>
<tr>
<td>Daily operational costs of trucks</td>
<td>EURO 8,000</td>
</tr>
<tr>
<td>Daily operational costs of cranes</td>
<td>EURO 15,000</td>
</tr>
<tr>
<td>Forfeit</td>
<td>0.028333 (1/300 \times 8.5)%</td>
</tr>
<tr>
<td>Daily lost income</td>
<td>EURO 25,975</td>
</tr>
<tr>
<td>Delays</td>
<td>13±3, Days</td>
</tr>
</tbody>
</table>

**Table III.** Additional input parameters for the model

![Figure 6](image-url)  
**Figure 6.** The distributed assessment of construction risks from Monte Carlo experiment

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Count</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Median</th>
<th>StDev</th>
<th>(Norm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPV vs initial time sensitivity results at time 5 Runs: Current</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“NPV vs initial time”</td>
<td>20,000</td>
<td>5.406 M</td>
<td>6.828 M</td>
<td>6.156 M</td>
<td>6.156 M</td>
<td>246,300</td>
<td>0.04001</td>
</tr>
</tbody>
</table>
4.4 Proposal for the mitigation of construction risks

In order to mitigate the risks of delay in materials supply that result in the postponement of commissioning the whole construction project, the contractor may increase the levels of safety stocks (SS) and correspondently targeted IL. In particular, if it is possible to estimate average deviations in the lead time from the supplier, the SS and ROP for IL in the warehouse of the contractor can be calculated by the formula (i.e. for the case when both demand and lead time are variables; Lukinskiy et al., 2017):

$$\text{ROP} = d \times L + x \sqrt{L \times \sigma^2_L + d^2 \times \sigma^2_s}.$$  \hspace{1cm} (2)

It should be noted that the use of this formula, which includes safety stock, in a “minimum-maximum” policy with a continuous review of ILs, helps to prevent project delay. However, it is only suitable for routine materials, when the mean demand is quite stable, but entails uncertainty in terms of quantity and lead time. If the delay is caused by unique materials that are only needed in a few projects, such an approach would not be appropriate.

Moreover, it is important to note that in the case using inventory control policies with ROP, i.e., when the replenishment order is made, if IL reaches ROP, the probability of stock deficit is very low, and with a continuous review system, it is excluded. Accordingly, for the calculation of the safety stock levels, included in both formulas of ROP, the deviation in the demand should be taken into account only during the lead time (L), and not the whole period (Lukinskiy et al., 2017).

By setting this formula in the discrete-event model, the circumstances of the deviation in the lead time (three days from the mean of five days) was considered (Figure 7).

As can be seen from Figure 7, the SS and targeted IL increased to 77 and 170 tons, respectively, from the risk scenario (SS = 21 and IL = 116). This enables the owner to avoid risks of stockouts (Figure 8) and, therefore, the risk relating to time and cost for the construction project.

For the contractor, this means that the warehousing expenses grow, on the one hand, but on the other hand, the fines due to undelivered material to the construction sites would decrease. In particular, if we assume that the contractor leases the warehouse and the cost of leasing 1 square meter is EURO 460, and that 1 ton of stored material corresponds to 3 square meters, then the expenses of the contractor increase by 74,520 EUR/year.
At the same time, if we consider that due to stockouts, the contractor experiences the same level of fines as the supplier (EURO 1,000 per undelivered ton of material to the construction site), its expenses will decrease by EURO 179,000±54 (as stockouts, calculated from Table II will be eliminated).

5. Conclusion
At the beginning of construction project, it is necessary to consider supply chain risks, such as possible delays in the supply of materials and other resources, overcapacity or deficiency warehouse, on-time loading and shipment of goods. These risks can be divided between the owner and the contractor, but no rigid line can be drawn. The participants are interdependent, and both can benefit economically from the success of the project.

Both qualitative and quantitative methods were used. In the present study, a combination of MCA with dynamic simulation was performed, using Vensim and AnyLogic programs. This answered the first research question:

\textit{RQ1.} What models and methods are suitable for the economic appraisal of construction project delays?

Dynamic simulation helped to portray the dynamic nature of the delays in the delivery of materials to the construction sites and the probability of the disruption in the construction supply chain. By contrast, the Monte Carlo method would not have been as effective, since it does not have an explicit time representation. The MCA, in turn, was thus used to calculate the parameter of NPV and DPP, as decision-making criteria corresponding to changes in the environment during the project realization. Its exposure to the construction risks was accessed by computing standard deviations from both capital-budgeting models (NPV and DPP).

With the help of a statistical analysis of models output, distributed values of NPV and DPP were obtained, rather than point values. Such an approach is especially suitable in the field of the construction, where there is uncertainty of information and material flows, resulting in inaccurate predictions and calculations. Moreover, difficulties in planning construction projects bring variability to the information and material flows, causing inefficiency in downstream processes. This results in delays, increases costs and restricts the use of lean principles.

The outcomes of the financial flow model, the minimum, mean and maximum possible NPV and DPP, were duly obtained. For this construction project of a container terminal, in the given scenario with risks, the NPV was 6.156, 5.406 and 6.828 ML EUR, respectively, with a standard deviation of 0.246 ML EUR. Applying the rule of three-$\sigma$ to the simulation results, it was found that when the probability is close to zero, the NPV is below 5.406 ML EUR.
The second critical capital-appraisal decision-making criterion (DPP) showed that, in the high-risk scenario, the investment will pay off in 3 years and 8.5 months. However, with a probability of 95 percent, the planned time can deviate from the average figure by ±2.1 months or within the confidence interval (3 years 6.4 months; 3 years 10.6 months). Thus, the analyses stress that by ignoring the risk scenario in the feasibility study for a construction project, investors and contractors can misjudge the future situation and face an over-expenditure of time and exceed the allocated budget.

For the owner, it is necessary to assess the risks inherent to the economic appraisal, in order to reduce cost overruns and avoid postponement of the project commissioning. Once the risk is measured in the feasibility studies, they can be managed in advance. The risks management aspects are addressed in the second research question:

RQ2. How can construction delays regarding time risks and cost risks be assessed and mitigated by a combination of different methods?

In order to mitigate the risks from construction delays, it was proposed to increase the safety stock of construction materials at the distribution center, which otherwise led to barrier disruption in the supply chain. In terms of practical implications (especially, for the contractor), it is necessary to find the right level of safety stock and the corresponding target ILs, allowing a reduction of stockouts and untimely delivery of the material to the construction site.

From the findings, it is evident that the overall outcomes were indeed largely generated by using suitable methods. This is an important theoretical implication of this study. Such an approach enabled excluding the maximum number of shortcomings of each method. However, the benefits of using both approaches, with respect to the research problem, were applied only to one research setting (i.e. for the hypothetical project). Thus, empirical data from similar and other research settings should be gathered to reinforce and confirm the validity of the reported findings. Another limitation is that the developed simulation models consider a simple supply chain with a single supplier. In a real scenario, multi-tier suppliers are involved in a construction project.

Therefore, in future studies, it would be useful to extend this model by including additional actors and factors that incur in the context of construction risks. At the same time, other groups of construction risks should be considered, in order to propose solutions for their mitigation. Another area of study could entail the distribution of risks over different project participants, especially if developed within the framework of public-private partnership investments.

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An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks

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Abstract

Purpose – Since the handling of environmentally sensitive products requires close monitoring under prescribed conditions throughout the supply chain, it is essential to manage specific supply chain risks, i.e. maintaining good environmental conditions, and ensuring occupational safety in the cold environment. The purpose of this paper is to propose an Internet of Things (IoT)-based risk monitoring system (IoTRMS) for controlling product quality and occupational safety risks in cold chains. Real-time product monitoring and risk assessment in personal occupational safety can be then effectively established throughout the entire cold chain.

Design/methodology/approach – In the design of IoTRMS, there are three major components for risk monitoring in cold chains, namely: wireless sensor network; cloud database services; and fuzzy logic approach. The wireless sensor network is deployed to collect ambient environmental conditions automatically, and the collected information is then managed and applied to a product quality degradation model in the cloud database. The fuzzy logic approach is applied in evaluating the cold-associated occupational safety risk of the different cold chain parties considering specific personal health status. To examine the performance of the proposed system, a cold chain service provider is selected for conducting a comparative analysis before and after applying the IoTRMS.

Findings – The real-time environmental monitoring ensures that the products handled within the desired conditions, namely temperature, humidity and lighting intensity so that any violation of the handling requirements is visible among all cold chain parties. In addition, for cold warehouses and rooms in different cold chain facilities, the personal occupational safety risk assessment is established by considering the surrounding environment and the operators' personal health status. The frequency of occupational safety risks occurring, including cold-related accidents and injuries, can be greatly reduced. In addition, worker satisfaction and operational efficiency are improved. Therefore, it provides a solid foundation for assessing and identifying product quality and occupational safety risks in cold chain activities.

Originality/value – The cold chain is developed for managing environmentally sensitive products in the right conditions. Most studies found that the risks in cold chain are related to the fluctuation of environmental conditions, resulting in poor product quality and negative influences on consumer health. In addition, there is a lack of occupational safety risk consideration for those who work in cold environments. Therefore, this paper proposes IoTRMS to contribute the area of risk monitoring by means of the IoT application and artificial intelligence techniques. The risk assessment and identification can be effectively established, resulting in secure product quality and appropriate occupational safety management.

Keywords Internet of things, Fuzzy logic, Cold chain, Wireless sensor network, Risk monitoring

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1. Introduction
Cold chain management (CCM) has been growing in the past few decades. Unlike traditional supply chain management, the goods in cold chains, such as pharmaceutical products, chilled food and frozen food, generally have a shorter shelf life and higher sensitivity to the surrounding environment, i.e. temperature, humidity and lighting intensity (Gormley et al., 2000). It thus requires certain refrigeration and dehumidification systems throughout the entire cold chain in order to maintain the prescribed environmental conditions. In particular, the ambient temperature for handling goods in a cold chain varies from $-25^\circ C$ to $+10^\circ C$, depending on the type of goods (Lana et al., 2005; Soyer et al., 2010). However, when handling goods in an environment with such a low temperature, special attention should be paid to the potential risks that may directly affect the product quality and operational efficiency. Companies may suffer loss if any potential risks emerge along the cold chain. For instance, in 2017, Lucky’s Market tossed all temperature-sensitive food, including cheese, juices and fresh cut meat, because they were stored at 16$^\circ C$ ($\sim60^\circ F$), and could not meet the storage requirement for keeping the products below 40$^\circ F$ (Nerbovig, 2017). About 1 in 6 Americans get foodborne illness annually from tainted food which is handled under improper temperature (Wein, 2014). On the other hand, excessive exposure of food handlers to a cold environment may cause serious health effects and contribute to accidents of death and injuries (Rice, 2014). In total, 15 workers died and 26 workers were injured at a Shanghai cold storage facility due to unexpected ammonia leakage (Laurence, 2013). The above reported cases show that the occurrence of cold chain risks affects not only the product quality and consumer health, but also the safety of personnel who work in the cold environment. Therefore, an effective risk monitoring system, especially for: product quality risk; and occupational safety risk, is vital to track and evaluate the levels of risk throughout the cold chain. In general, product quality risk is the degree to which a product does not satisfy customers’ requirements that is caused by product deterioration and contamination throughout the cold chain; occupational safety risk is the degree of exposure to workplace hazards, such as an extraordinary cold environment, among different supply chain facilities.

Figure 1 shows a typical cold chain, and the existing problems, for handing frozen food. Among the entire cold chain, it is important to ensure that the products are stored and handled under the proper environmental conditions for maintaining good product quality. Any abnormal environmental changes should be visible and realized by all other cold chain parties. As shown in the figure, each party would perform individual quality checking when receiving goods. However, without the environmental information that is shared by the upstream supply chain parties, only the goods arrival temperature can be measured. There is a chance that the goods have already deteriorated or been contaminated during handling by other parties or during the transportation. Real time environmental monitoring and control is deemed to be essential to increase product visibility and traceability with the related parties in the cold chain. The Internet of Things (IoT) is a global structured network for interconnecting everyday objects which are equipped with intelligence, identification, and sensing technologies (Yang, 2014). By applying the IoT paradigm, products and surrounding conditions in the cold chain can be tracked and traced automatically, resulting in transparent CCM. In addition, the quality degradation can be measured in a real-time manner.

On the other hand, depending on the product type, the condition of working environment has to be kept constantly at a low temperature. For example, chilled food should be kept at 0—10$^\circ C$ while frozen food should be kept below $-15^\circ C$. To work under such environment with low temperature, there is a high likelihood of certain occupational safety risks, including cold-related illnesses (e.g. asthma and rhinorrhea), cold-related symptoms (e.g. wheezing and chest pain), and cold injuries (e.g. frostbite and trench foot) (Mäkinen and Hassi, 2009). The occurrence of occupational safety risks would directly affect the working performance of staff, resulting in a decrease in operation efficiency,
workplace comfort and safety. The industrial common practice “ISO11079” is currently adopted for improving the ergonomics in cold environments. It is an ergonomics measurement to determine the thermal stress with exposure to a cold environment, called cold stress (ISO/TC 11079, 2007). The required clothing insulation (IREQ), recommended exposure time ($D_{lim}$) and recovery time (RT) are calculated when working in the cold environment. However, this practice does not consider the personal health status so that the formulated risk management may be inappropriate for assessing and identifying the risks in the workplace. Under the IoT environment, certain sensor nodes, such as wearables and environmental sensors, can be applied to collect personal health data to enhance the existing occupational safety measurement. Consequently, the risk assessment and identification regarding occupational safety can be formulated through the use of artificial intelligence (AI) techniques.

With the structured infrastructure of the sensor network in IoT and robust computations in AI, the integration of IoT and AI is a promising way to establish risk monitoring systems in the cold chain. In this paper, an IoT-based risk monitoring system (IoTRMS) is proposed to fill the research gap of ineffective risk monitoring and management for product quality and occupational safety in cold chains. The purpose of this study is; to formulate an IoT system framework to measure product quality; and to integrate an effective fuzzy logic approach with the IoT system to enhance the practice of ISO11079. Cold chain parties will then be able to check the report on all previous environmental data regarding the products, after receiving the goods. In addition, each cold chain party can establish its own occupational safety risk management plan based on the specific ambient environment and workers’ health status. Through the adoption of IoTRMS, the product quality can be ensured throughout the entire cold chain, and the personal occupational safety risk can be effectively mitigated for the cold chain parties. The significance of this study is to integrate IoT paradigm and AI techniques in the field of cold chain risk management. In addition, this study contributes to all cold supply chain parties involved, including the farmer, processer, distributor and retailer, so as to manage its product quality risk and occupational safety risk through measuring the product
quality degradation and enhancing ISO11079 practice under the IoT environment. Therefore, workplace ergonomics are improved, while the product quality throughout the cold chain is maintained and is measurable.

This paper is organized as follows. Section 1 is the introduction. Section 2 reviews the literatures related to cold chain, risk management, IoT applications and AI techniques. Section 3 presents the system architecture of IoTRMS. A case study of the proposed system and implementation roadmap are presented in Section 4. Section 5 gives the results and discussion of the advantages and limitations of the proposed system. Finally, conclusions are drawn in the Section 6.

2. Literature review
Supply chain management is an extended concept of logistics management, which aims at enhancing the linkage and coordination between various interdependent parties, such as suppliers, processors, distributors and customers (Christopher, 2016; Chung et al., 2018). The key objective of logistics and supply chain management is to plan and coordinate the material and information flow from the source to users in an integrated and effective manner. Catering to environmentally sensitive products in the material flow, CCM is established to maintain the desired product quality so as to achieve specific handling requirements by using particular refrigeration and dehumidification systems (Joshi et al., 2011). According to the 2016 Top Markets Report of Cold Supply Chain issued by International Trade Administration, the refrigerated warehouse and transportation are two significant components in the cold chain (Miller, 2016). The refrigerated warehouse capacities in India, China and Mexico were increased by 43, 35 and 27 percent from 2008 to 2014, respectively, implying that the demand for cold chain services is sustainably increasing globally. Inside the cold chain, technologies for controlling the environment play an important role in providing ideal conditions for products so that the likelihood of product deterioration and contamination can be reduced. However, the supply chain is vulnerable due to internal and external risks, including supply risk, demand risk, process risk, control risk and environmental risk (Christopher, 2016). The assessment of the vulnerability can be evaluated by multiplying the probability of disruption and impact, and the results can be used in identifying the risk profile of a company. Hence, the appropriate control measures and possible consequences can be formulated. Regarding cold chain activities, there are two additional risk considerations compared to the general supply chain management, namely: maintaining products under specific ranges of environmental conditions; and occupational safety in the cold environment. Laguerre et al. (2013) summarized seven major stages for the material flow in cold chains, namely transportation, warehousing, logistics hub, cold room, retail display cabinet, and the domestic refrigerator of customers. On the one hand, warehousing is an important section among all cold chain parties, and is a closed environment applying refrigeration systems to meet the handling requirements. The workers are at risk in completing all warehousing operations when exposure to a cold environment. On the other hand, without real-time traceability, it is difficult to ensure that the products which are moved along the cold chain are maintained in stable prescribed environmental conditions (Aung and Chang, 2014). Therefore, the risk assessment, identification and monitoring for product quality risk and occupational safety risk in cold chains is particularly essential.

In cold chains, risk management should prevent exposure to undesired temperature and humidity, as product deterioration and contamination may result. Tse and Tan (2011) stated that the product quality risk is harmful to consumers in producing unsafe products in the supply chain, and, in fact, exists at any tier of the supply chain network. The visibility of the risk in the supply chain is important to enhance the product quality. The importance of real-time inventory monitoring and asset visibility is emphasized in maintaining
appropriate levels of product quality and determining minimal managerial costs (Kelepouri et al., 2007; Montanari, 2008; Nakandala et al., 2016). Furthermore, recent research discussed the development of cold chain monitoring systems by means of radio frequency identification (RFID) technology for beverages, fruits, horticultural, and fishery products (Abad et al., 2009; Lao et al., 2012; Lam et al., 2013; Ting et al., 2014; Kim et al., 2016). It shows that the product categories in cold chain are varied, and the products themselves are environmentally sensitive. Although RFID technologies are able to identify the products and record ambient environmental conditions, the product quality in terms of shelf life may worsen due to changes of temperature (Rong et al., 2011). Expired shelf life may cause product deterioration and contamination leading, for example, to foodborne illness. Product quality degradation is a main concern in customers’ acceptance, and it should be seriously controlled in the cold chain (Ling et al., 2015), otherwise, the product quality can be below the acceptance level, resulting in wastage and spoilage issues. Besides, storage and transportation environmental conditions are sometimes extraordinarily low, according to the handling requirements, and there is a potential risk in the workplace related to occupational safety. Human factors and occupational safety risks are important, but receive limited consideration in supply chain management (Skjoett-Larsen, 2000; Gowen II and Tallon, 2003; Chan and Chan, 2011). As cold chain facilities operate at a low temperature, the comfort design and operational processes should be focused on maintaining productivity and the operators’ safety. Occupation safety risk management is used to prevent workplace hazards which can lead to physical and emotional hardship (Kitt and Howard, 2013). The ergonomics of the thermal condition is an essential workplace hazard factor impacting on the efficiency and effectiveness of the logistics operations (Epstein and Moran, 2006; Balaras et al., 2007). Mäkinen and Hassi (2009) generally defined temperature range of cold work at/below +10 to +15°C. In real-life situations, the temperature of cold chain facilities may vary from −40 to +10°C, depended on the type of inventory handled. Apart from the climatic factors, the safety and health effect of the cold conditions is also contributed by physical activity, clothing, individual constitution, and socioeconomic factors. Inappropriate risk management for cold exposure may trigger cold-related diseases and aggravate the symptoms of chronic diseases. The above studies focused on state-of-the-art technologies to provide functionalities on incident management, cold chain monitoring, and traceability in order to maintain the desired product quality. However, there was a lack of the consideration of risk mitigation related to product quality risk throughout the entire cold chain. In addition, there have been limited studies on occupational safety risk management in cold chains, particularly considering of individual constitutions, i.e. health status.

Under the IoT environment, smart objects with integrating wireless communication technologies, sensors and actuators can connect to the internet and share their data, in order to provide real-time data acquisition in supply chain management (Wortmann and Flüchter, 2015; Yan et al., 2016). The fundamental architecture of IoT consists of four layers, namely the sensing layer, gateway/network layer, management service layer and application layer (Dweekat et al., 2017; Rezaei et al., 2017). Compared with RFID technology, IoT is an expanded concept that emerged from the prerequisite of RFID foundation (Jia et al., 2012). Apart from developing the automatic data capturing technology, an IoT-based system has a structured network infrastructure for connecting both physical and virtual objects in order to enhance the capability of data capturing, event transfer, network connectivity and interoperability. Wearable technology has been developed to reflect the actual personal health status for further analytics, while several sensors are integrated to collect real-time bio-signals, such as heart rates, body/skin temperature and blood pressure (Pantelopoulos and Bourbakis, 2010). Other sensor technologies, such as temperature sensors, can be applied to build a wireless sensor network in order to monitor warehouse environmental conditions (Wu et al., 2015). In recent years, the feasibility of M2M protocols, such as IPv6
Recent research shows that different AI techniques have been applied in occupational safety management to aid domain experts in making decisions, including case-based reasoning, analytic hierarchy processing and association rule mining (Virikki-Hatakka and Reniers, 2009; Chen et al., 2010; Liao and Chiang, 2012). Among the above AI techniques, there was lack of capability in handling vague and uncertain variables, such as personal health status. Fuzzy logic is another promising AI technique for generating acceptable reasoning with uncertainty and vagueness by mimicking human thinking and decision-making processes. In practice, fuzzy logic has been widely applied in various scenarios. Markowski et al. (2009) explored the fuzzy logic approach in process safety analysis for accident risk assessment due to uncertain input data and inaccurate output process risk level. Beriha et al. (2012) proposed the adoption of fuzzy logic for prediction of various accidents in an uncertain environment. Saravanan et al. (2014) developed a fuzzy-based risk rating system to predict accident risk on road networks based on road condition, driver-based risk and the number of pedestrians crossing the road. Hence, it is deemed to be a suitable technique to enhance ISO11979 practice by combining personal constitutions to evaluate the appropriate levels of occupational safety risk.

With the above study, it can be summarized that product quality and occupational safety risk management are critical to the effectiveness and efficiency in cold chains. The existing ISO11079 measurement can be enhanced to provide a customization of occupational safety measurements, resulting in improvement of productivity. Hence, this study attempts to develop an IoT monitoring system integrated with the fuzzy logic approach, in which real-time environmental data can be collected, and personal occupational safety risk plans can be formulated for cold chain operators.

3. Design of the IoTRMS
This section proposes an IoTRMS for dynamic occupational safety management and real-time environmental monitoring. It can further estimate the occupational safety risk level and accident frequency rate so as to schedule an appropriate workforce level. The proposed system is divided into four modules, i.e. automatic data capturing, IoT service management, fuzzy occupational safety risk assessment, and dynamic risk management, as shown in Figure 2.

3.1 Module 1: automatic data capturing
This module shows the structure for collecting real-time data related to the operators’ health status and ambient environmental information. In the entire cold chain, cold facilities, workers and goods are three major elements, called “Things” in the IoT paradigm, among suppliers, processors, distributors and retailers for handling environmentally sensitive products, such as frozen meat and seafood. The environmental sensor, i.e. SensorTag CC2650, is deployed in every cold facility and cargo pallets so as to monitor the degree of temperature, humidity and light intensity. The real-time monitoring of the product and cold facility can be formulated throughout the cold chain. Moreover, the workers are equipped with wearable devices, i.e. Microsoft band 2, in order to monitor their health status in real-time. The SensorTag CC2650 and Microsoft band 2 are selected as the sensor nodes due to the high capability of cloud application programming interface (API) so as to convert real-time data in JavaScript Object Notation (JSON) format, and integrate the data into a cloud-based Platform as
a Service. Data from SensorTag CC2650 and Microsoft band 2 can be transmitted to the proposed system through IBM IoT registered service and Microsoft Health Cloud APIs, respectively. In addition, they are manufactured for collecting the ambient environment data, for example ambient temperature and humidity, and health data, for example heart rate. Hence, the IoT monitoring application is established to collect sensor data automatically for further analysis by means of AI techniques. As illustrated in Figure 3, the IoT technology stack for data acquisition is divided into three major layers, namely device layer, connectivity layer, and IoT cloud layer, called as the IoT technology stack.

In the device layer, the SensorTag CC2650 and Microsoft band 2 play the role of sensor nodes to collect real-time data, such as ambient temperature, humidity, light intensity, heart rate, and burned calories. Certain software and programs are flashed on the sensor nodes to operate the requested functionality, for example sensor listening frequency and data measurement intervals. The real-time collected data are then transmitted to the IoT cloud layer through M2M transmission protocols in the connectivity layer. The proposed sensor nodes are embedded in the Bluetooth wireless module for effective short-range data exchange. Particular to SensorTag CC2650, it also enables the capability of 6LoWPAN for
handling local data exchange and connection to the internet by using an arbitrary link, such as Wi-Fi and 3G/4G network. In addition, transmission protocols are developed for asynchronous messaging queues and point-to-point communication from sensor nodes to both front-end and back-end applications, for example MQTT and XMPP. In the IoT cloud layer, the IoT development platform, such as IBM Bluemix and Exosite, is applied to standardize the system development through providing device management, front-end and back-end development sources. Through registering the sensor nodes in the IoT platform, the collected data can be loaded in the cloud database with two additional functions, namely data analytics and process management, so the data pre-processing can be simply completed. By integrating the static data, including personal constitutions, cold accidents and ISO11079 measurement, a tailor-made IoT application is then developed to achieve the proposed objectives of IoTRMS, namely product monitoring reporting and occupational safety risk assessment. Consequently, cloud service security and integration with other business applications, such as warehouse management system (WMS), by using APIs are used to formulate a total IoT application. Therefore, the wireless sensor network with adopting low power sensing technologies, can be established.

### 3.2 Module 2: IoT service management

In this module, the real-time dynamic data are integrated with the static data in a cloud database under the IoT services. The cloud database is then connected to the existing WMS in order to create a product monitoring report by using specific time ID and product ID. Figure 4 shows the process of IoT system implementation starting from the sensor nodes to the end application. The sensors and corresponding devices are registered in the specific IoT service platform such that the data capturing function can be enabled.
The data are then transmitted to the platform in the formats of JSON/XML/HTML which are the common data formats for real-time data transmission. Through the authenticated cloud API service and certain logic building in the back-end process, the collected data can be managed in a cloud database. It is also capable of integrating with other data which have been pre-loaded in the database. Consequently, it can support the development of the proposed system in occupational safety risk management, including handling web event and querying. The cloud database contains not only dynamic sensor data, but also static data from real-life cold chain operations. Figure 5 shows the diagram for database structure for IoTRMS development, covering both dynamic and static data in the workplace. There are eight major data tables, namely product information (prodInfo), cold accident record (ColdAccident), personal constitution (Worker), ISO11079 measurement (ISO11079), environmental sensor data (ESensor), and personal health data (Health), equipment data (Clothing) and WMS. Apart from the typical data extraction, transformation and loading, the IoT service platform also enables usage monitoring and is integrated with NoSQL for achieving the complicated data transmission and management tasks. Therefore, all loaded data can be managed in an organized manner for formulating dynamic risk management in cold chains.

As the real-time environmental data are collected through the above IoT system, the product quality degradation model is embedded in this module to estimate the quality...
change for a specific time period. The proposed product quality degradation model is derived from the generic quality prediction as shown in the following equation:

\[
\frac{\Delta q}{\Delta t} = k q^n,
\]  

where \( q \) is the product quality; \( t \) the time; \( k \) the rate of quality gradation; and \( n \) the order of degradation reaction. The generic quality prediction model can be further derived by using the Arrhenius equation. Since a zero-order reaction is suitable to describe the temperature-dependent quality degradation, the product quality degradation model is therefore established with activation energy \( E_a \) and gas constant \( R \) to calculate the quality change, as shown in the following equation. In other words, the relationship between quality and time is linear:

\[
\Delta q(t, T) = -k_0 t e^{-\frac{E_a}{RT}}.
\]

The products in cold chains are moved along with supplier, processor, distributor, retailer and other sub-parties involved. Assuming that \( q_i(t, T) \) and shelf life \( s_i \) are partitioned into \( i \) equally sized, the maximum rate of product quality degradation is assigned and minimum shelf life is selected despite the fact that the ambient temperature fluctuates in the cold chain, i.e. max\{\( q_i(t, T) \}\} and min\{\( s_i \)\}.

### 3.3 Module 3: fuzzy occupational safety risk assessment

Since the cold chain operators have varying personal constitutions and work under extraordinary conditions, companies face challenges in providing adequate ergonomics design and risk assessment. This module proposes a fuzzy logic approach on occupational safety risk management, which is able to consider uncertain information in the system design. The input and output parameters in the assessment are related to personal constitutions, work experience, ISO11079 measurements and occupational safety risk. Decision makers in cold chains conveniently use linguistic terms, such as “high” and “low,” to express the relationship between the above input and output parameters. For instance, the occupational safety risk should be large for warehouse workers who are old and have poor in health. However, there is no detailed deterministic approach to judge the exact quantities on age and health conditions. The process in occupational safety risk assessment involves a range of possibilities of inputs to achieve the definite outputs. Therefore, the simple rule-based or non-fuzzy system may not be applicable such that the proposed system should be capable of handling the fuzziness of data to determine a personal ISO11079 measurement and occupational safety risk assessment for the cold chain service providers. The inference mechanism of adopting fuzzy membership functions and fuzzy rules is able to imitate human reasoning to provide a certain flexibility and levels of possibilities when integrating knowledge from domain experts in the companies. The required data are extracted from the cloud database under the IoT service platform so as to provide a real-time and dynamic fuzzy logic assessment. In addition, useful data assimilation and knowledge are jointly referred to and stored in the knowledge repository, where they are collected by interviews with domain experts and the data mining of historical data. The membership function of the specific fuzzy sets can be defined and used in the fuzzy rules, while it also contains the fuzzy IF-THEN rules for supporting fuzzy logic assessment. Overall, this module consists of three stages: fuzzification, inference engine, and defuzzification, in order to establish a dynamic occupational safety risk measurement for cold chain operators.

In the stage of fuzzification, the real-life input and output data are converted to the fuzzy data sets with a defined fuzzy class, such as “low,” “medium,” and “high,” etc., and degree of belongingness from 0 to 1, typically. In other words, there are two sets of data, namely input

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data with \( I = \{ I_1, I_2, I_3 \ldots I_n \} \) and output data with \( O = \{ O_1, O_2, O_3 \ldots, O_m \} \). The fuzzy set \( I_i \) of data set \( X \) is illustrated with its membership function as shown in the following equation:

\[
I_i = \sum_{i=1}^{n} \frac{\mu_A(X_i)}{X_i},
\]

where \( X_i \) shows the entire data set with all element \( \{ x_1, x_2, x_3, \ldots, x_n \} \); \( \mu_A(X_i) \) is the corresponding membership function of fuzzy class \( A \) of \( X_i \); \( n \) is the total number of sub-elements.

In the inference engine, the rule \( R = \{ R_1, R_2, R_3, \ldots, R_m \} \) is applied to evaluate the aggregated output of the fuzzy logic, where \( m \) is the total number of fuzzy rules. Figure 6 shows the composition of the fuzzy rules in the inference engine. The membership function can be the composition of various shapes of membership functions, the fuzzy classes for input \( (X_i) \) and output \( (Y_i) \) data are expressed in \( A_i^p \) and \( C_i^q \), respectively, where \( p \) and \( q \) are the total number of fuzzy classes for the input and output data. The mechanism of the inference engine is defined by Mamdani's method (Suthar et al., 2015), which gives the outputs in the form of a fuzzy set rather than a linear mathematical expression. Since the set of input and output parameters has been fuzzified using (1), the value of membership functions can be evaluated according to the antecedent and consequence of given fuzzy rules. By applying \( m \) fuzzy rules in the inference engine, the membership function values of the aggregated output can be defined as (4). The OR operator is then applied for combining all membership function values in the consequence part, so that the bounded area in membership function can be established:

\[
\mu_C(Y_i) = \max \left\{ \min_i \left[ \mu_{A_{i1}}(X_1), \mu_{A_{i2}}(X_2), \ldots, \mu_{A_{ir}}(X_r) \right] \right\}.
\]

In the stage of defuzzification, the fuzzy sets are converted back and aggregated to crisp numerical and linguistic values. In practice, there are numeric defuzzification methods, such as bisector and centroid defuzzification, among which the centroid method, also called as center of gravity, is one the most popular methods for obtaining fuzzy output results. The following equation shows the mathematical expression for the centroid method of
combined output parameters. It is expected that, by using the fuzzy logic approach, the personal occupational safety risk measurements and prediction of cold risks can be achieved:

\[
\overline{Y}_i = \frac{\int_{1}^{n} Y_i \mu_C(Y_i) dY}{\int_{1}^{n} \mu_C(Y_i) dY}.
\]  

(5)

In order to assess and validate the rules in the proposed fuzzy logic approach, a measure quality \(Q(R, I)\) is introduced to classify the performance of the outputs by using the set of input \(I\) and set of rules \(R\). Although the rules and membership functions are formulated by the domain experts who have sufficient field experience and knowledge, the performance may not be applicable to the real-life situations. First, the rule redundancy is assessed by investigating the change of measure quality after counting an addition rule \(r\), i.e. \(Q(R \cup \{r\}, I) - Q(R, I)\). If the change of measure quality is less than zero, the additional rule is redundant in the inference engine generates the applicable reasoning. Second, the measure quality is also applied to validate the rules and the proposed fuzzy logic approach (Mahalakshmi and Ganesan, 2015). By partitioning the input data set \(I\) into \(i\) equally sized sets \(I_i\), the measure quality is applied individually to investigate the output performance judged by the domain expert, i.e. \(q_i = Q(R, I_i)\). The system performance of the proposed system is then calculated by dividing the number of satisfactory results by the total number of subjects considered in the proposed system.

3.4 Module 4: dynamic risk management

Based on the results from the IoT service management and fuzzy occupational safety risk assessment, a dynamic risk management can be established with three major functionalities, namely: environment and health status monitoring; personal occupational safety risk planning; and mobile/web-based application. Figure 7 shows the output overview of IoTRMS throughout the entire cold chain. Inside the IoT development platform, several logic and threshold values can be embedded in the system design such that environmental and health status can be kept track of in a real-time manner. Once there is any violation of the defined threshold values, a prompt alert and warning can be sent to the operators and on-site supervisors. In addition, the proposed system can generate a specific product monitoring report for the cold chain parties in order to make sure that the previous product handling processes meet the requirements. On the other hand, IoTRMS can generate the personal risk profile for each cold chain party according to their uploaded dynamic and static data in the cloud database. The personal risk profile covers the personal occupational safety risk measurement, i.e. recommended exposure time, IREQ, and RT, and prediction of
frequency of three types of cold risks, i.e. cold injuries, cold associated illness, and
fatality/disability. Table I shows the potential effects of above cold risks. By doing so, the
supervisor and management level can estimate the effective workforce level and
potential medical compensation costs. In order to create a user-friendly application, a
mobile/web-based application is developed by integrating the above two functionalities.
Web-socket is applied to transmit the real-time dynamic data from back-end to front-end
application, while PHP and JavaScript are adopted to embed the fuzzy logic assessment
for illustrating the occupational safety risk planning to end users.

4. Case study
In order to validate the feasibility and performance of IoTRMS, a case study was conducted in a
cold chain that particularly for handled frozen and fresh food. One of the cold chain parties, as
the role of distributor, was selected for illustrating the mechanism of the proposed system. ABC
Limited has ambitions for providing customized and one-stop logistics solutions covering the
cold chain business. It has strategic and close collaboration with other cold chain parties, with an
18-storey, 28,000 metric tons capacity building for supporting cold chain businesses. The storage
facility includes both freezing (−25°C to −18°C) and chilling (0°C to 8°C), while it also owns
number of refrigerated trucks for delivery. Plates 1 and 2 show the freezing and chilling sections
in the case company. The major logistics operations are performed under such environmental
conditions, including put-away, order picking and packing. In order to provide the best cold
chain services, the logistics premises comply international standard of ISO9001:2008. Therefore,
the operational workflow is standardized so as to deliver high productivity and efficiency in cold
chain operations. Since the facility scale is not suitable for adopting automation in logistics
operations, the operations presently highly rely on available human resources.

In order to further consolidate its leading position in cold chain industry and deal with
the ever-changing business environment, the company attempts to monitor the goods
throughout the cold chain and to improve the ergonomics in such a labor-intensive
workplace. However, due to diversified personal health status and lack of real-time
environmental data acquisition, the company has difficulty in establishing effective risk
management for mitigating product and occupational safety risks. In general, the problems
which the company are facing are summarized as follows:

(1) only checking the product temperature at the point of goods receiving is not reliable;
(2) the personal constitution and health status of cold chain operators differ, and there is
a lack of dynamic occupational safety risk management for assessing the risk level
and suggesting the personal planning; and
(3) the prediction of cold risks is lacking in the cold chain so that the workforce stability
and performance are very uncertain.

Due to facing these problems, ABC Limited decided to conduct a pilot study on the IoTRMS
in the cold storage and distribution center for three months, with the aim of total product
monitoring and minimizing occupational safety risks in logistics operations. Consequently,

<table>
<thead>
<tr>
<th>Types of cold risk</th>
<th>Causes</th>
<th>Potential effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cold injuries</td>
<td>Frostbite, hypothermia, trench foot</td>
<td>Temporary disability, lose a few working days</td>
</tr>
<tr>
<td>Cold-related illness</td>
<td>Asthma, Chronic Obstructive Pulmonary Disease, cold urticarial</td>
<td>Partial disability, long-term treatment required</td>
</tr>
<tr>
<td>Fatality/disability</td>
<td>Serious hypothermia</td>
<td>Death, permanent disability</td>
</tr>
</tbody>
</table>

Table I. Potential effect of cold risks
an implementation flow of IoTRMS is proposed with four major phases as shown in Figure 8, namely sensor network deployment, IoT system development, integration with fuzzy logic approach, and establishment of dynamic risk management. Consequently, the IoTRMS was implemented with outputs of real-time product monitoring and personal occupational safety risk planning.

4.1 Phase 1: sensor network deployment
In this phase, the low power wireless sensor network (LPWSN) is established by the use of SensorTag CC2650 and Microsoft band 2 for collecting environmental data and personal health status. The implementation procedures of the LPWSN can be divided into sensor installation and edge router deployment. In ABC Limited, the sensor nodes of SensorTag CC2650 are installed in cold facility, clothing ensembles, and goods pallets; the sensor nodes of Microsoft band 2 are given to each worker who is required to work inside the cold facility. Figure 9 illustrates the installation of the sensor nodes, including SensorTag and Microsoft band 2, in the case company. The SensorTag is embedded into the collar of the jackets in order to collect the ambient environmental conditions of the workers. For installing the sensor nodes in goods pallets, the SensorTag is attached to the goods for monitoring the temperature, humidity and light intensity. For the cold facility, the sensor nodes are placed in the corners of the facility so that the overall environmental conditions of temperature and humidity can be measured effectively. The average values of temperature and humidity are inputted to the ISO11079 measurement to compute the original recommended exposure duration and RT. In order to facilitate the data transmission and synchronization, an edge router is also required.
Low power wireless sensor network
Sensor Installation
Edge router for data transmission
Fuzzy logic approach
Input and output determination
Fuzzy membership functions
Extraction of fuzzy rules

Phase 1: Sensor network deployment
Phase 2: IoT system development
Phase 3: Integration with fuzzy logic approach
Phase 4: Establishment of dynamic risk management

IoT monitoring system
Development in IoT platform
Mobile/web application
Output of IoT RMS
Real-time product monitoring
Personal occupational risk planning

Figure 8. Implementation flow of IoT RMS in ABC Limited

Plate 2. Chilling section in ABC Limited

Figure 9. Implementation procedure of IoT technologies

Microsoft band 2
SensorTag CC2650

Sensor Deployment
Wearing by workers
Collar of the jackets
Cold facility
Pallet of goods

Sensor Node Configuration Process
Create client ID and secret in Microsoft Health Cloud APIs/Waston IoT platform
Register the sensor nodes to return API token or other authentications
Configure the token to the specific sensor nodes
Add the credentials to the IBM Bluemix

IoT RMS
for conversion between the sensor network and standard IP header. A smart phone, i.e. iPhone SE, which is set as the master device, is selected for this role by using a Bluetooth connection with the mentioned sensor nodes. By configuring the sensor nodes through the Microsoft Health Cloud API and IBM IoTF registered service in the edge router, the data can be transmitted to the proposed system in a real-time manner. Therefore, the deployment of LPWSN was completed in the case company. By integrating the advantages of IPv6 and IEEE 802.15.4, the 6LoWPAN provides effective internet and internal data exchange so as to support several open IP standards and mesh routing development. Figure 10 shows the transmitted and organized data from both sensor nodes in the JSON format under RFC 4627 standard. It includes sensor data from the SensorTag and Microsoft band 2, namely ambient temperature, object temperature, humidity, lighting level, heart rate summary, and calories burned summary. Due to handling the data from different sensor nodes, the data parsing is required to consistently convert some string data to integer data, such as ambient temperature. With such structured data format, the data can be loaded onto the SQL server for the fuzzy logic approach and monitoring functionality.

4.2 Phase 2: IoT system development

For the development of IoT-RMS, one of the well-known IoT development platform, i.e. IBM Bluemix, is selected to construct the device layer, connectivity layer, as well as IoT system architecture. Figure 10 shows an example of dynamic data in JSON format.
cloud layer. The required sensor nodes are registered under its device management tool, i.e. IBM Watson IoT Platform. The simplified gateway communication can be created for real-time data transmission. Inside the Bluemix platform, it supports multiple programming languages for application development with the online library, such as JavaScript and PHP. By integrating the static data stored in MySQL database, the data can be loaded to the mobile or web-based applications by using WebSocket. Therefore, the end users, i.e. operators and managers in the case company, are able to monitor the real-time environmental and health information. The alert function can also be enabled by simply defining the conditions and threshold values of the collected data. In the proposed system, the users, i.e. operators, supervisors, and managers, are able to measure and predict the occupational safety risks for their cold chain facilities. The functionalities of product monitoring and occupational safety risk management are embedded for authorized users in the system.

Apart from the real-time monitoring, fresh meat is handled in the case company with its supply chain partners. Given that the shelf life of fresh meat will be reduced from five to three days when temperature increases from −2.8°C to 3°C, following the linear characteristics between quality in term of shelf life and temperature, the shelf life decrease per unit of temperature is 0.35 days/°C. Table II shows estimated shelf life and rate of quality degradation for fresh meat in the cold chain. Since the average ambient temperatures among supplier, processor, distributor and retailer are different, the shelf life of the fresh meat is measured to estimate the remaining days for the fresh meat. For example, according to the zero-order degradation nature, the change of shelf life from the supplier side to the processor side is 7 − (−3.8 − (−8.3)) × 0.35 = 5.4 days. Even though the average temperature in the distributor is increased to −6.9°C, the shelf life should be changed by selecting the smallest possible shelf life, i.e. min{5.4, 5.4 − (−6.9 − (−3.8)) × 0.35}. Therefore, the shelf life remains unchanged in order to estimate the shelf life conservatively and maintain a good product quality before reaching the customers. In order to distinguish the rate of quality degradation, a total quality level of 100 is used in this situation. The rate of quality degradation is calculated by considering the linear relationship of zero-order reaction between product quality and shelf life, i.e. the quality is degraded over the time spent in supply chain activities. For example, the rate of quality degradation in supplier is estimated at (100 − 0)/(0 − 7) = −14.3. Therefore, it enables the cold chain parties to estimate the product quality throughout the entire cold chain.

For the sake of applying fuzzy logic to measure the occupational safety risk in a cold chain facility, the company’s database also stores the criteria of membership functions and fuzzy rules. However, in the past, the adoption of the fuzzy logic approach faced challenges related to ineffective membership functions and fuzzy rules so that the fuzzy applications performance fluctuated. In the proposed system, the IoT service platform enables the effective and efficient information exchange across various cold chain partners, while the performance and settings of the fuzzy applications can be shared in real-time. Figure 11 shows the information flow of the occupational safety risks, performance and settings of the fuzzy applications. The wearables and sensors are provided for every operator in each cold chain party, and the data are stored in its own database. Through the cloud service, there is a centralized cloud database for collecting all the information so as to extract the application

| Table II. Estimation of shelf life and rate of quality degradation for fresh meat |
|--------------------------|--------|--------|--------|--------|
| Stage                  | Supplier (S) | Processor (P) | Distributor (D) | Retailer (R) |
| Average temperature (°C) | −8.3 | −3.8 | −6.9 | −0.7 |
| Shelf life (days)       | 7     | 5.4  | 5.4  | 4.3   |
| Rate of quality degradation | −14.3 | −18.5 | −18.5 | −23.26 |
settings for relatively good performance. Therefore, the domain expert can analyze the information in order to fine-tune the defined fuzzy applications, and the system performance can be maintained at an acceptable level.

4.3 Phase 3: integration with fuzzy logic approach

According to the defined fuzzy membership functions and fuzzy rules, the fuzzy logic approach can be developed in order to enhance the ISO11079 measurement. Since the ISO11079 measurement has the assumption of fixed personal constitutions, the measurement outputs, i.e. recommended exposure time and RT, are insufficient. In addition, the relationship between work experience, constitutions and occupational safety risks is difficult to be formulated in a simple prediction manner. Therefore, the fuzzy logic approach is deemed to be a feasible solution to provide adjustments to ISO11079 and the occupational safety risk.

Prior to defining membership functions and fuzzy rules, there are five input parameters, i.e. body mass index \( B \), age \( A \), average heart rate (avgHR), average calories burnt (avgCB) and work experience \( E \), and four output parameters, i.e. percentage change of recommended exposure time \( D_{\text{lim}} \) and RT, hazard severity (HS) of cold risks (HS) and likelihood of occurrence of cold risks (LO), for the fuzzy logic. Figure 12 shows the structure of fuzzy logic assessment with the above five inputs and four outputs.

Each parameter is then fuzzified by the membership functions such that number of fuzzy classes and its distribution can be defined for the process in the inference engine and defuzzification. Tables III and IV show the parameters, units, fuzzy classes, membership function regions and shapes of membership functions for the inputs and outputs, respectively.

For the input parameters, the body mass index \( B \) and average calories burned (avgCB) are defined as \( \{L, \text{RL}, A, \text{RH}, H\} \), where \( L \) is Low, \( \text{RL} \) is relatively low, \( A \) is average, \( \text{RH} \) is relatively high, and \( H \) is high. The age \( A \) is defined as \( \{Y, \text{RY}, A, \text{RO}, O\} \), where \( Y \) is...
young, $RY$ is relatively young, $A$ is average, $RO$ is relatively old, and $O$ is old. The average heart rate (avgHR) is defined as \{S, RS, A, RF, F\}, where $S$ is slow, $RS$ is relatively slow, $A$ is average, $RF$ is relatively fast, and $F$ is fast. The work experience ($E$) is defined as \{L, A, H\}, where $L$ is low, $A$ is average, and $H$ is high. For the output parameters, the percentage change of recommended exposure time ($D_{lim}$) is defined as \{SuD, SiD, SlD, N, SlI, SiI, SuI\}, where $SuD$ is substantially decrease, $SiD$ is significantly decrease, $SlD$ is slightly decrease, $N$ is no change, $SlI$ is slightly increase, $SiI$ is significantly increase, and $SuI$ is substantially increase. The HS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Fuzzy class</th>
<th>Region</th>
<th>Shape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Body mass index ($B$)</td>
<td>kg/m$^2$</td>
<td>$L$</td>
<td>(14.5, 14.5, 15.5, 16)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RL$</td>
<td>(15.5, 16, 16.5)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$A$</td>
<td>(16, 16.5, 22.5, 23)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RH$</td>
<td>(22.5, 23, 25)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$H$</td>
<td>(23, 25, 30, 30)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td>Age ($A$)</td>
<td>years</td>
<td>$Y$</td>
<td>(18, 18, 25)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RY$</td>
<td>(18, 25, 30, 33)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$A$</td>
<td>(30, 33, 45, 50)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$O$</td>
<td>(45, 50, 55)</td>
<td>Triangular</td>
</tr>
<tr>
<td>Average heart rate (avgHR)</td>
<td>bpm</td>
<td>$S$</td>
<td>(40, 40, 50)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RS$</td>
<td>(40, 50, 60)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$A$</td>
<td>(50, 60, 70, 80)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RF$</td>
<td>(70, 80, 90)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$F$</td>
<td>(80, 90, 120)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td>Average calories burnt (avgCB)</td>
<td>kcal</td>
<td>$L$</td>
<td>(0.6, 0.6, 0.8)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RL$</td>
<td>(0.6, 0.8, 1)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$A$</td>
<td>(0.8, 1, 1.2, 1.4)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$RH$</td>
<td>(1.2, 1.4, 1.6)</td>
<td>Triangular</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$H$</td>
<td>(1.4, 1.6, 2, 2)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td>Work experience ($E$)</td>
<td>years</td>
<td>$L$</td>
<td>(0, 0, 1, 3)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$A$</td>
<td>(1, 3, 8, 10)</td>
<td>Trapezoid</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$H$</td>
<td>(8, 10, 20, 20)</td>
<td>Trapezoid</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Fuzzy class</th>
<th>Region</th>
<th>Shape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage change of recommended exposure time ($D_{lim}$)</td>
<td>%</td>
<td>$SuD$</td>
<td>(-1, -0.75, -0.5)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$SiD$</td>
<td>(-0.75, -0.5, -0.25)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$SlD$</td>
<td>(-0.5, -0.25, 0)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$N$</td>
<td>(-0.25, 0, 0.25)</td>
<td>Triangle</td>
</tr>
<tr>
<td>Percentage change of recovery time (RT)</td>
<td></td>
<td>$SlI$</td>
<td>(0, 0.25, 0.5)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$SiI$</td>
<td>(0.25, 0.5, 0.75)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$SuI$</td>
<td>(0.5, 0.75, 1)</td>
<td>Triangle</td>
</tr>
<tr>
<td>Hazard severity of cold risks (HS)</td>
<td>1-5</td>
<td>$FA$</td>
<td>(1, 1, 2)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$I$</td>
<td>(1, 2, 3)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$DI$</td>
<td>(2, 3, 4)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$PDI$</td>
<td>(3, 4, 5)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$FI$</td>
<td>(4, 5, 5)</td>
<td>Triangle</td>
</tr>
<tr>
<td>Likelihood of occurrence of cold risks (LO)</td>
<td>1-5</td>
<td>$S$</td>
<td>(1, 1, 2)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$O$</td>
<td>(1, 2, 3)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$L$</td>
<td>(2, 3, 4)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$NC$</td>
<td>(3, 4, 5)</td>
<td>Triangle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$C$</td>
<td>(4, 5, 5)</td>
<td>Triangle</td>
</tr>
</tbody>
</table>

**Table III.** Fuzzification conversion for input parameters

**Table IV.** Fuzzification conversion for output parameters
is defined by five-point scale with \{FA, I, DI, PDI, FI\}, where FA is first aid attempt, I is injury causing time off, DI is disabling injury, PDI is permanent disabling injury, and FI is fatal injury. Similarly, likelihood of occurrence (LO) is defined as \{S, O, L, NC, C\}, where S is seldom, O is occasional, L is likely, NC is near certain, and C is certain.

Regarding the shapes of the membership functions, the trapezoidal and triangular types are determined intuitively from a group of domain experts in cold chains according to their intelligence, understanding and experience. The intuitive method is capable of considering contextual and semantic knowledge to the system design so that the degree of freedom to formulate the membership functions is sufficiently large. Therefore, in the case company, the trapezoidal and triangular shapes are used to interpret the input and output parameters. On the other hand, there are total 45 fuzzy rules in the format of IF-THEN rules which are obtained from the domain experts as well. All the rules are stored in the knowledge repository and applied in the inference engine.

4.4 Phase 4: establishment of dynamic risk management

In the case company, information on eight staff is extracted to evaluate their cold risks and suggest corresponding personal risk profiles so as to mitigate the cold risks in the proposed system, as shown in Table V. They are all working in the staging area which is a chilled environment at around 2°C. In general, the company provides specific insulated jackets to the operators, but the operators are dissatisfied with the current occupational safety risk management associated with cold exposure workplace.

In order to illustrate the mechanism of IoTRMS, worker W0001 is used to show the computation of fuzzy logic assessment. Worker W0001 has a BMI of 24.5 kg/m², 42 years old, 82 average daily heart rate, 1.433 average calories burned in working hours, and 5.25 years of relevant work experience. Through the fuzzification process, the corresponding membership values can be shown for the five input parameters, as shown in Figure 13.

In BMI (B), the value 24.5 kg/m² cuts the fuzzy classes RH and H at membership values 0.25 and 0.75, respectively. In average heart rate (avgHR), the value 82 bpm cuts the fuzzy classes RF and F at membership values 0.80 and 0.20, respectively. In average calories burned (avgCB), the value 1.433 kcal cuts the fuzzy classes RH and H at membership values 0.835 and 0.165, respectively. In age (A) and work experience (E), the values 42 years and 5.25 years also cut the fuzzy class A in its corresponding membership functions so that their membership values are 1. In the IF-THEN rule-based repository, the successful rules are fired for compositing the membership values in W0001 in order that it can generate the membership values of the output parameters. The six corresponding rules are extracted with their composition result shown in Table VI. Fuzzy set theory is a systematic approach for knowledge conversion in a non-linear mapping mechanism. The smallest membership value of the specific input parameter is obtained as the composition result. Through aggregating with the output membership functions, the fuzzy sets can be

<table>
<thead>
<tr>
<th>Staff ID</th>
<th>Input parameter</th>
<th>avgHR</th>
<th>avgCB</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>W0001</td>
<td>24.5</td>
<td>42</td>
<td>82</td>
<td>1.433</td>
</tr>
<tr>
<td>W0002</td>
<td>21.2</td>
<td>25</td>
<td>69</td>
<td>1.687</td>
</tr>
<tr>
<td>W0003</td>
<td>26.0</td>
<td>31</td>
<td>76</td>
<td>1.593</td>
</tr>
<tr>
<td>W0004</td>
<td>20.5</td>
<td>20</td>
<td>65</td>
<td>1.836</td>
</tr>
<tr>
<td>W0005</td>
<td>24.2</td>
<td>49</td>
<td>79</td>
<td>1.413</td>
</tr>
<tr>
<td>W0006</td>
<td>29.0</td>
<td>55</td>
<td>89</td>
<td>1.382</td>
</tr>
<tr>
<td>W0007</td>
<td>27.6</td>
<td>39</td>
<td>75</td>
<td>1.501</td>
</tr>
<tr>
<td>W0008</td>
<td>22.8</td>
<td>24</td>
<td>62</td>
<td>1.567</td>
</tr>
</tbody>
</table>

Table V. Input parameters for fuzzy logic approach
turned into crisp values for the decision-making process by using the mentioned centroid method. In this process, the largest membership value of the specific output parameter is extracted to determine the center of gravity in the area of the bounded region. Figure 14 shows the four bounded output membership functions for worker W0001. The percentage change of $D_{lim}$ is $-38.1\%$, percentage change of RT is $41.6\%$, HS is $2.37$, and LO is $3.45$. For the sake of establishing the personal occupational safety risk planning for
each operator, the knowledge repository is expanded with sufficient rules which are extracted from the IoT environment. The useful rules are then fired and extracted for the fuzzy logic assessment. By repeating the above steps for all the other operators, the crisp output values for all eight operators are summarized in the Table VII. Reasonable and personal ISO11079 measurements can be generated, while the occupational safety risk level associated with cold exposure can be evaluated by multiplying HS and LO.

5. Results and discussion

As shown in Table VII, according to the outputs from the fuzzy logic approach, the percentage change of recommended exposure time, RT, HS and likelihood of occurrence can be generated. As mentioned above, the workplace temperature is at 2°C so that it is implied that the mean radiant temperature of warehouse workers is almost 2°C. In addition, the humidity for the environment is set at 50 percent and the available basic clothing insulation is given at 1.5 clo. Regarding the logistics operations, the operators require certain hand work and arm work to handle the goods so that their metabolic energy production is estimated at 100 W/m² based on ISO8996. Therefore, a fixed set of ISO11079 measurements including minimal and neutral recommended exposure time and RT, is calculated. The selection between two proposed recommended exposure times are based on the level of physiological strain on the operators. On the other hand, by multiplying HS and likelihood of occurrence, the risk level can be

<table>
<thead>
<tr>
<th>Staff ID</th>
<th>% of $D_{\text{lim}}$</th>
<th>Personal minimal $D_{\text{lim}}$ (hr)</th>
<th>Personal neutral $D_{\text{lim}}$ (hr)</th>
<th>% of RT</th>
<th>Personal RT (hr)</th>
<th>HS</th>
<th>LO</th>
<th>Risk level</th>
</tr>
</thead>
<tbody>
<tr>
<td>W0001</td>
<td>−0.381</td>
<td>1.55</td>
<td>0.74</td>
<td>0.416</td>
<td>1.27</td>
<td>2.37</td>
<td>3.45</td>
<td>8.18</td>
</tr>
<tr>
<td>W0002</td>
<td>0.25</td>
<td>3.13</td>
<td>1.50</td>
<td>−0.5</td>
<td>0.45</td>
<td>1.32</td>
<td>1.32</td>
<td>1.74</td>
</tr>
<tr>
<td>W0003</td>
<td>−0.122</td>
<td>2.20</td>
<td>1.65</td>
<td>0.25</td>
<td>1.13</td>
<td>1.48</td>
<td>2.98</td>
<td>4.41</td>
</tr>
<tr>
<td>W0004</td>
<td>0.24</td>
<td>3.10</td>
<td>1.49</td>
<td>−0.169</td>
<td>0.75</td>
<td>1.34</td>
<td>1.72</td>
<td>2.30</td>
</tr>
<tr>
<td>W0005</td>
<td>−0.25</td>
<td>1.88</td>
<td>0.90</td>
<td>0.324</td>
<td>1.19</td>
<td>1.44</td>
<td>3.3</td>
<td>4.75</td>
</tr>
<tr>
<td>W0006</td>
<td>−0.5</td>
<td>1.25</td>
<td>0.60</td>
<td>0.75</td>
<td>1.58</td>
<td>4</td>
<td>3</td>
<td>12.00</td>
</tr>
<tr>
<td>W0007</td>
<td>−0.25</td>
<td>1.88</td>
<td>0.90</td>
<td>0.5</td>
<td>1.35</td>
<td>1.38</td>
<td>4</td>
<td>5.52</td>
</tr>
<tr>
<td>W0008</td>
<td>0.351</td>
<td>3.38</td>
<td>1.62</td>
<td>−0.435</td>
<td>0.51</td>
<td>1.4</td>
<td>1.4</td>
<td>1.96</td>
</tr>
</tbody>
</table>

Table VII. Output parameters of the fuzzy logic approach
estimated for assessing their risks in cold chain operations. Figure 14 shows the occupational safety risk assessment chart for the mentioned eight operators with the corresponding HS, likelihood of occurrence and risk level. There are generally three sections of risk level, in red, orange and green colors, which represent the dangerous, urgent and normal zones. The three risk levels are partitioned by 40 percent in normal, 20 percent in urgent and 40 percent in dangerous zones, which follow the general practice of risk assessment in the case company. Operators 2, 3, 4, 5, and 8 are classified in the normal zone; operators 1 and 7 are classified in the urgent zone; operator 6 is classified in the dangerous zone. To sum up, it is found that operator 6 is regarded as the highest risk level in the case study, and therefore the prompt action and appropriate care should be taken to mitigate the risks. Moreover, operators 1 and 7 have the second and third highest risk levels in the orange region. The line supervisors and managers should be informed about this issue and take appropriate care actions. Others are measured within the normal risk level and the protection and risk planning are reasonably practicable (Figure 15).

Further, the fuzzy occupational safety risk assessment is validated through the assessment and validation procedures stated in module 3 of the proposed system. The classification of the measure quality is divided into three dimensions, i.e. satisfied, moderate, and unsatisfied. Table VIII shows the validation of the results obtained from the IoTRMS. For obtaining the results for each staff in the case company, the corresponding active fuzzy rules are extracted from the knowledge repository. The domain expert who is knowledgeable and experienced in cold chain operations is required to assess the outputs through assigning the appropriate measure quality classification. For the IoTRMS, seven out of eight results are classified as satisfied, and the remaining result is classified as moderate. It is concluded that 87.5 percent of

<table>
<thead>
<tr>
<th>Staff ID</th>
<th>Active rules</th>
<th>Measure quality classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>W0001</td>
<td>6, 7, 8, 21, 22, 23</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0002</td>
<td>1, 11, 19, 26, 28, 29</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0003</td>
<td>9, 10, 13</td>
<td>Moderate</td>
</tr>
<tr>
<td>W0004</td>
<td>1, 11, 13, 19, 27, 28, 29</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0005</td>
<td>32, 35, 36, 41, 43</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0006</td>
<td>26, 29, 30, 36, 38</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0007</td>
<td>31, 32, 37, 42, 43, 44</td>
<td>Satisfied</td>
</tr>
<tr>
<td>W0008</td>
<td>15, 18, 32, 36, 37</td>
<td>Satisfied</td>
</tr>
</tbody>
</table>

System Performance 87.5%
the industrial experts are satisfied with the results so that the proposed system is deemed to be appropriate for real-life applications.

Apart from discussing the mitigation of occupational safety risk, the product quality risk is controlled in the proposed system through the adoptions of: IoT monitoring; and the quality degradation model. On the one hand, the environmental sensor, i.e. SensorTag CC2650, which is attached in the goods pallet is able to collect the ambient temperature and humidity in real-time for monitoring the handling condition of the goods. An alarm will be triggered to the relevant cold chain parties if there is a violation of the handling requirements. The transparency when handling the goods in both warehousing and transportation is therefore enhanced. On the other hand, due to the characteristics of the quality degradation mentioned in Section 3, the product quality can be quantified by considering the average handling temperature and the corresponding shelf life. Ideally, the case company, and other cold chain companies, attempt to maintain the stability of the ambient environmental conditions throughout the entire cold chain. However, in the real-life situation, due to different facilities and operation procedures, fluctuation of environmental conditions cannot be avoided. Therefore, the estimated shelf life and rate of quality degradation become known to all the stakeholders in the cold chain.

5.1 Dashboard of IoTRMS

Since the static data are handled in the cloud-based database structured by using SQL, and dynamic data are transmitted by using WebSocket to the proposed system, IoTRMS enables both product monitoring and occupational safety risk assessment functionalities. In view of the IoTRMS dashboard, there are two major sections, namely: environmental monitoring; and occupational safety risk management. Figure 16 shows the user interface of the environmental monitoring in the proposed system. After user configuration in the dashboard, there are three functions, i.e. real-time site temperature, environmental conditions in specific intervals and incident management. The real-time temperatures at different sites in the cold chain are displayed, and the data are stored in the cloud database. Users can generate a report in a specific time interval, and then export into Excel or CSV format for recording and reporting. Once there is a violation of the environmental conditions, the details are shown in the Feeds

![Dashboard of IoTRMS](image-url)

**Figure 16.** User interface of environmental monitoring in IoTRMS
section, helping users realize the key incidents for the entire cold chain activities. Figure 17 shows another user interface of the occupational safety risk assessment in the proposed system. The users are required to connect their pre-stored data from the database by using their own worker ID. The input data can then be extracted for the fuzzy occupational safety risk assessment so as to estimate four outputs, namely: recommended exposure time; RT; HS; and risk likelihood. The corresponding risk level of W0005 is then shown marked by the triangular shape in the below risk assessment chart.

5.2 Discussion of IoT-based risk management in cold chain

According to the measured performance of the proposed system in Table IX, the product quality and occupational safety risks can be mitigated so as to improve the ergonomics and provide total product monitoring. Under the IoT environment, the data and related information can be exchanged in real-time, which enables various cold chain parties to formulate tailor-made product quality and occupational safety risk management. In summary, IoTRMS obtains three areas of significant benefit to cold chain parties as follows.

Occupational safety risk mitigation in cold chain premises. The IoTRMS provides personal occupational safety risk planning to each operator in cold chain premises, with suggested recommended exposure time, RT and corresponding actions in handling cold

<table>
<thead>
<tr>
<th>No.</th>
<th>Area</th>
<th>Measuring unit</th>
<th>Before implementation</th>
<th>After implementation</th>
<th>Percentage of improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>Accident frequency rate</td>
<td>Number/month</td>
<td>10</td>
<td>4</td>
<td>60</td>
</tr>
<tr>
<td>ii</td>
<td>Average staff satisfaction</td>
<td>Scale (0-10)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>6.78</td>
<td>8.13</td>
<td>19.9</td>
</tr>
<tr>
<td>iii</td>
<td>Order fulfillment rate</td>
<td>Order/Total order</td>
<td>0.78</td>
<td>0.89</td>
<td>14.1</td>
</tr>
<tr>
<td>iv</td>
<td>Idle time for recovery&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Minutes/day</td>
<td>60</td>
<td>75</td>
<td>−25</td>
</tr>
<tr>
<td>v</td>
<td>Workforce stability</td>
<td>Available workforce/Total workforce</td>
<td>0.84</td>
<td>0.95</td>
<td>13.1</td>
</tr>
</tbody>
</table>

Notes: <sup>a</sup>10 is highest comfort in scale, while 1 is the lowest comfort in scale; <sup>b</sup>the idle time mainly refers to the time for recovery after leaving the cold workplace

Figure 17. User interface of occupational safety risk management in IoTRMS
accidents and injuries. The proposed system simplifies the effort in ergonomics and comfort design for ease of use, so that the companies are able to adopt the methods in a user-friendly manner. By integrating the foundation of ISO11079 measurement, IoT and fuzzy logic, the occupational safety risk level can be examined in a structured risk assessment chart in return for risk minimization and mitigation. It can greatly reduce the reliance on human judgment and monitoring. In the fuzzy logic assessment on ISO11079 measurement and risk assessment, the proposed cloud services enable the centralized storage and sharing of pre-requisite membership functions and fuzzy rule knowledge so that various cold chain parties can easily establish the most suitable fuzzy inference engine. Hence, the occupational safety risk can be certainly mitigated and minimized.

**Improvement of operational efficiency and employee scheduling.** As mentioned above, the implementation of IoTRMS aims at reduction of the accident frequency rate and improvement of the operational efficiency through real-time monitoring and the fuzzy logic approach. Table IX shows the performance comparison between before and after implementing IoTRMS in the case company. There are five areas for assessing the system performance, namely accident frequency rate, average staff satisfaction, order fulfillment rate, idle time for recovery and workforce stability. Since the proposed system generates personal occupational safety risk planning for each operator, they can be sufficiently protected by the systematic instructions and monitoring. In view of that, the accident frequency rate recorded an improvement with 60 percent in the reduction of the number of accidents and injuries. However, the idle time for recovery is slightly increased by 25 percent as the existing RT for the operators is insufficient. For the logistics operations, most of the employees are satisfied with the proposed system which can create a safe and comfortable working atmosphere in the company. As a consequence, it is beneficial to the order fulfillment rate with a 14.1 percent improvement. In addition, since the HS and likelihood of occurrence can be estimated, it can foresee possible cold accidents and injuries. Apart from providing appropriate care to the operators, the supervisors and managers are also able to assign additional workers for maintaining the normal workforce level. As a result, the workforce stability is improved by 13.1 percent.

**Enhancement in cold chain monitoring and visibility.** Without the adoption of IoTRMS, companies do not have real-time data gathering and transmission regarding the environmental and personal health information. The monitoring is generally done by data loggers which are inefficient for handling tens of thousands of goods at the same time. The IoT application provides the capability for handling real-time events, such as data capturing and data analytics, in return for better visibility in the cold chain. Therefore, various cold chain parties can generate a product monitoring report at the point of goods receiving so that the possibility of product deterioration and contamination can be reduced. It can be seen as evidence for maintaining the right conditions of the products. Besides, the membership function settings and fuzzy rule knowledge are shared among various cold chain parties. They can access the above data and information for establishing their own occupational safety risk management and for viewing the status of the premises and workers. The use of IoTRMS also aids companies to set the specific key performance indexes related to safety and health-related incidents. Consequently, effective warehouse management can be maintained, and hence the decision-making process in occupational safety risk management can be reliable and systematic throughout the cold chain network.

5.3 Managerial implications
Food harm scandals, such as food poisoning due to improper storage conditions, and industrial accidents, such as cold accidents due to excessive exposure to cold environments, indicates that product quality and occupational safety are vulnerable in cold chain networks. For the supply chain parties, improper risk monitoring and management for product quality risk and
occupational safety risk damages company reputation, gives a weak competitive edge, and high accident frequency rates. Therefore, companies are willing to invest in certain risk assessment tools which follow national or international standards, such as the Health and Safety Executive in the UK. In the absence of interconnectivity and interoperability in risk management systems, the risks in cold chains are not fully visible and transparent in minimizing the threats to quality and safety. In the IoT environment, the IoT system is able to connect physical and virtual objects by sensing technologies, cloud computing and AI techniques to enhance the visibility and traceability. The cold chain parties can take advantage from the IoT to improve the visibility of products in regard to product information, ambient environmental conditions and expected product quality. On the other hand, the knowledge repository where the knowledge is extracted from the domain expert from one company can be inter-communicated with the others. The deployment of a knowledge repository is changed from a stand-alone task to a shared task. It benefits the companies in establishing an effective knowledge repository for the application of fuzzy logic in occupational safety risk assessment. Some organizations who lack expertise are also able to deploy the knowledge repository as well as the entire decision support system. Therefore, product quality risk and occupational safety risk can be effectively managed in global cold chain networks.

6. Conclusions

With respect to handling environmentally sensitive products in supply chains, risk management is important in preventing product loss and industrial accidents. On the one hand, there is a probability that the products will either deteriorate or be contaminated at any point in cold chain due to the fluctuation of temperature and humidity. Cold chain parties may bear unnecessary loss if visible product monitoring information is not recorded. On the other hand, most operations and processes are labor-intensive, whereas the operators have to work under demanding environments. Without appropriate risk assessment and management, it may result in cold-associated accidents and injuries, even fatality. In such a sense, the cold chain parties need to develop an automatic system for occupational safety risk management in order to establish better ergonomics and comfort design in the premises. In this paper, an IoTRMS is described. Under the IoT environment, the SensorTag CC2650 and Microsoft band 2 as the sensor nodes are applied to collect the real-time environmental and health-related data. The IBM Bluemix is used to build the application for IoTRMS for real-time and automatic monitoring. Based on the collected environmental data, the product shelf life and rate of quality degradation can be estimated. In order to establish the personal occupational safety risk assessment, the fuzzy logic approach is integrated to enhance the ISO11079 measurement and risk level in cold chains. Through the application of IoT, the corresponding data and information can be shared throughout the entire cold chain so as to achieve better cold chain visibility. Unlike typical fuzzy logic-based systems, the proposed IoTRMS takes advantage of the effective data exchange in IoT to investigate the most appropriate membership functions and fuzzy rule knowledge. Therefore, with the aid of IoTRMS for the various cold chain parties, risk management in product quality and occupational safety can be executed effectively and efficiently. Decision makers can adopt appropriate strategies in maintaining desired product quality and reducing the accident frequency rate. This study provides an applicable method for improving product quality risk and occupational safety risk management in cold chains, where it also contributes to the research on cold chain monitoring and industrial safety. Furthermore, other sources of relevant data can be fine-tuned and collected for fulfilling the needs of different industries. The limitations of this study are: requirement of full internet coverage for implementing the proposed system; and reliance of the knowledge collected from the domain expert for the application in fuzzy logic approach. Future work of this study should further enhance the system adaptability through integrating with other AI and data mining techniques, such as genetic algorithms and fuzzy association rule mining.
References


Further reading


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A fuzzy-based House of Risk assessment method for manufacturers in global supply chains
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Abstract

Purpose – Risk management is crucial for all organizations, especially those in the global supply chain network. Failure may result in huge economic losses and damage to company reputation. Risk assessment usually involves quantitative and qualitative decisions. The purpose of this paper is to apply fuzzy logic to capture and inference qualitative decisions made in the House of Risk (HOR) assessment method.

Design/methodology/approach – In the existing HOR model, aggregate risk potential (ARP) is calculated by the risk event times the risk agent value and its occurrence. However, these values are usually obtained from interviews, which may involve subjective decisions. To overcome this shortcoming, a fuzzy-based approach is proposed to calculate ARP instead of the current deterministic approach.

Findings – Risk analyses are conducted in five major categories of risk sources: internal, global environment, supplier, customer and third-party logistics provider. Moreover, each category is further divided into different sub-categories. The results indicate that the fuzzy-based HOR successfully inferences the inputs of the risk event, risk agents and its occurrence, and can prioritize the risk agents in order to take proactive decisions.

Practical implications – The proposed fuzzy-based HOR model can be used practically by manufacturers in the global supply chain. It provides a framework for decision makers to systematically analyze the potential risks in different categories.

Originality/value – The proposed fuzzy-based HOR approach improves the traditional approach by more precise modeling of the qualitative decision-making process. It contributes to a more accurate reflection of the real situation that manufacturers are facing.

Keywords Risk management, Risk assessment, Global supply chain, Risk analysis, House of Risk

Paper type Research paper

1. Introduction

According to ISO, Guide 73 (2009), risk is defined as an effect which is “a deviation from the expected—positive and/or negative.” No doubt that risk should refer to the negative side, e.g. hazard risks and uncertainty risks. It is known that risk is defined as a combination of the consequences of an event and the associated likelihood. In reference to the definition of risk management (RM), it should be the coordination of different activities in order to direct and control an organization with regard to risk (Wang 2009). Similarly, Fone and Young (2000) noted that RM could be taken as a function for general management so that managers could evaluate risks in order to achieve a firm’s overall objectives.

Traditionally, RM involves two major processes: occurrence identification and evaluation, and consequences identification and evaluation. Smallman (1996) held the view that the process is not necessarily formal and structured in effective RM while common sense toward risk is more essential. Whereas in academia, there is a tendency to a more formalized and structured methodology for managing risks (Cox and Townsend, 1998; Khan and Burnes, 2007; Chung et al., 2017). White (1995) pointed out that most approaches toward RM include three critical stages: risk identification, risk estimation and risk evaluation. Later on, Sople (2012) further proposed four processes in RM: identify risk, measure risk, manage risk and monitor risk.
In general, RM techniques involve three approaches: qualitative, quantitative and control. The qualitative technique aims at identifying, describing, analyzing and understanding risks. The quantitative technique aims at modeling risk to quantify the corresponding effects. The control technique aims at identifying risk to minimize risk exposure (Simon et al., 1997; Khan and Burnes, 2007).

In this paper, we use the House of Risk (HOR) framework developed by Pujawan and Geraldin (2009) to propose a fuzzy logic approach for the interpretation of the aggregate risk potential (ARP). The rest of the paper is organized as follows. Section 2 gives the relevant literature on risk identification and assessment methods. Section 3 presents the mechanism of the proposed fuzzy-based HOR. Section 4 discusses the case studies and the corresponding findings. Finally, the paper is concluded in Section 5.

2. Supply chain risk management (SCRM)

Manufacturers in a global supply chain usually face risks arising from different aspects, including internal and external factors (Chung et al., 2011; Sun et al., 2015). The risk in a supply chain has gained more attention as it has become the major factor affecting the supply chain performance (Jüttner and Helen, 2003). Supply chain risks can turn out to be a series of negative outcomes in various areas of the supply chain, including sales, customer service, operations, marketing and supply. The outcomes include overordering, inaccurate forecasting, overproducing, long buffer of delivery, delay in new product launches, etc. (Christopher and Lee, 2004).

SCRM concerns the risk assessments of activities at both strategic (long-term) and operational (short-term) levels (Lavastre et al., 2012; Chung et al., 2013). SCRM has become crucial in recent years (Tse et al., 2016; Trkmak et al., 2016). The risks involved are usually modifiable or preventable (e.g. information flow, materials flow), or occurring between organizations along a global supply chain. Be more specific, it can be further categorized into risk identification, supply chain risk categories and supply chain risk analytic framework.

2.1 Risk identification

Risk identification is a vital first step for any RM activity, and is also critical to the successful SCRM. There are many approaches for risk identification. Tummala et al. (1994) stated several methods to identify potential supply chain risks: event tree analysis, checklists or check sheets, supply chain mapping, failure mode and effect analysis (FMEA), fault tree analysis and cause and effect analysis. Singhal et al. (2011) classified different approaches into the following: the common listing approach, in which it is based on the historical events to analyze and gain insight into future risks; the taxonomy-based approach, which identifies and organizes risk activities based on different business functions with a consistent framework; the scenario analysis, where the risk profile is developed by analyzing the key risk factors and their impacts on the supply chain performance so as to develop contingency plans; and risk mapping, in which the potential risks are listed by analyzing the vulnerability of the supply chain.

2.2 Risk categorization

Supply chain risk categories refer to the classification of different types of risks in the supply chain. Different categorization may have a different focus on the analysis of the supply chain risk. Effective categorization is crucial for identifying risks precisely and in developing contingency plans properly. However, in the supply chain domain, there is no well-established way to classify risks. The grouping of risks, therefore, is very complicated and diversified.

Some studies stated that the supply chain risks can be categorized based on internal and external sources (e.g. Goh et al., 2007; Kiser and Cantrell, 2006; Christopher and Peck, 2004).
Tang (2006) noted that there should be two types of supply chain risk: operational risks and disruption risks. The operational risks can be regarded as the risks coming from the supply chain itself, e.g., uncertain supply, uncertain demand and uncertain cost. Disruption risks are normally led by the natural or man-made disasters, e.g., hurricanes, earthquakes, floods, fire and so on. Goh et al. (2007) pointed out that supply chain risks can be categorized into two types according to their sources: internal supply chain network and the external environments. Shub et al. (1994) argued that risks can be categorized according to scheduling, technological and cost uncertainty. Sinha et al. (2004) observed that the main elements leading to supply chain risk are insufficient trust, information asymmetry, over relying on outsourcing and inflexible contracts.

Wong (2014) reviewed the RM literature between 1999 and 2012, and proposed that past studies on supply chain risks can be grouped according to four classifications: role; organization structure; operations; and sources and types. Roles are defined as suppliers, internal and the customers’ risks (Douglas, 2007). Risks can also be classified according to three levels: application level, organization level and inter-organizational level (Finch, 2004). For operations, it can be categorized to source, make, deliver and return risks, and these business processes can be further divided into sub-processes to figure out the real cause (Puwan and Geraldin, 2009; Musa, 2012). Risks can be grouped as seven types: price risk, quantity risk, quality risk, technology risk, economic risk, environmental risk, process risk, management risk, chaos risk and inventory risk (Matook et al., 2009; Norrman and Jansson, 2010). In short, Wong (2014) recommended that risks should be categorized according to the flow of materials: supply risks, manufacturing risks, distribution risks and external risks.

2.3 Supply chain risk analytic framework
A framework named the Risk Management Process (RMP) was developed by Tummala et al. (1994), which included five phases: “risk identification, risk measurement, risk assessment, risk evaluation and risk control and monitoring.” This framework has been very successful in identifying the seriousness of relevant consequences and in developing proper risk mitigating strategies (Burchett and Tummala, 1998). To identify, evaluate and cope with supply chain risks, Finch (2004), Manuj and Mentzer (2008) and Tummala and Schoenherr (2011) have conducted research, proposing a modified RMP, which can be regarded as the “Supply Chain Risk Management Process”—an instrument which provides supply chain managers with helpful information by considering various supply chain risks in different situations.

3. Proposed fuzzy HOR assessment method
HOR is regarded as a proactive model, and consists of two major parts: FMEA and House of Quality (HOQ). Its idea is to prioritize the significant cause of supply chain risk and the most cost-effective mitigation measures.

In the FMEA, the severity, occurrence and detection of a list of risk events are taken as the decisive factors to calculate the RPN, which is used to prioritize the listed risk events. Risk events refer to events that have the possibility to go wrong in a certain business process. For example, transportation disruption could be a risk event that has the possibility to occur in the delivery process (Chung et al., 2015).

Unlike FMEA, in the HOR model, the severity of the risk events and the occurrence of the risk agents, which are the possible causes of the risk events, are the decisive factors to prioritize the listed risk agents. A risk agent is regarded as the direct cause of one or more than one risk event. For example, “inaccurate information exchanged among departments” could be one of the major causes that induce the risk event “wrong item sent to customer” (Ruel et al., 2017). Note that one risk event could be induced by more than one risk agent and one agent may lead to a number of risk events. Besides, the relation between each risk event and the risk agent is also a key figure in the model (Puwan and Geraldin, 2009).
Pujawan and Geraldin (2009) adapted the HOQ model to prioritize risk agents by assigning a rank to each risk agent according to the ARP, which is known as the aggregation of risk potential of the \( j \)th risk agent. The idea is to allow an organization to visualize the highest risk activities for the sake of RM. In addition, the HOR model also focuses on prioritizing the proactive actions for those prioritized risk agents by comparing the cost-effectiveness of the action. Thus, the HOR model is composed of two major parts: HOR1 and HOR2 as outlined in Figure 1.

3.1 Fuzzy modeling of risk event
The ultimate goal of HOR1 is to prioritize the risk agents in order to assign proactive actions according to their significance. Thus, the first step is to identify the risk events (\( E_i \)). As our aim is to study the risks of manufacturers in a global supply chain, we adopt the framework proposed by The Supply Chain Council (SCC) Risk Research Team (2008) to partition the business process into five segments: plan, source, make, deliver and return as follows:

1. Plan: the processes which make demand and supply balanced to develop a series of activities so as to best fulfill the requirements of sourcing, production and delivery.
2. Source: the processes that purchase services and goods so as to satisfy the planned or practical demand.
3. Make: the processes which transform inward goods to finished products so as to satisfy the planned or practical demand.
4. Deliver: the processes that offer finished products and services so as to satisfy the planned or practical demand, which normally include logistic management, order management and distribution management.
5. Return: the processes that deal with any returned or returning goods.

Identification and assessment (\( S_i \)) of risk events (\( E_i \))
Identification and assessment (\( O_j \)) of risk agents (\( A_j \))
Develop relationship matrix (\( R_{ij} \)) between each \( E_i \) and each \( A_j \)
Calculate the aggregate risk potential (ARP\( j \))
Prioritize risk agents using Pareto Diagram
Propose proactive actions (PA\( k \)) for the risk agents
Develop relationship matrix for \( A_j \) and PA\( k \)

Figure 1. Outline of House of Risk model
Each process can be further divided into several sub-processes, and the possibility of risk events in each sub-process should be identified. Traditionally, the severity $S_i$ of a risk event is on a ten-point scale system, with 10 representing the most severe one (Pujawan and Geraldin, 2009). However, assigning a severity value is a subjective qualitative decision. Precisely assigning a value to represent a risk event is in fact infeasible and impractical. Thus, we propose fuzzy expression. $S_i$, which is classified as very low (VL), low (L), normal (N), severe (S) and very severe (VS) as shown in Figure 2.

3.2 Fuzzy modeling of risk agents
Similarly, for risk agents, based on The SCC Risk Research Team (2008) framework, we identify the risk agents in terms of internal, global environment, supplier, customer and third party. In past studies, the risk agents would be prioritized according to their respective occurrence $O_j$, in which, the occurrence is assigned using a ten-point scale. Same as the assignment of severity of a risk event, this is subjective decision. In fact, the occurrence can be measured by analyzing the historical data and then converting into a quantitative value. Therefore, we propose a fuzzy expression for its representation. $O_j$ is classified as less (L), normal (N) and frequent (F). Based on the occurrence in the historical results, we normalize the number of occurrences and use 0.5 as the normal. Figure 3 shows all the fuzzy input sets.

3.3 Modeling of relationship between risk event and risk agent
We use $R_{ij}$ to model the correlation between $S_i$ and $O_j$. Again, this is a subjective decision. It is also classified into low (L), medium (M) and high (H), as shown in Figure 4.

3.4 Defuzzification—modeling of APR
Based on the fuzzy input sets, we model the fuzzy output of the risk assessment result. Again, the risk level is classified into low (L), medium (M), high (H) and very high (VH) as shown in Figure 5. For defuzzification of risk agent $j$ to a particular risk event $i$ under the
occurrence $j$, we apply center of gravity, which is widely used in the literature for fuzzy defuzzification (Bowles and Pelaez (1995), as shown in the following equation. We model the output value in the range of 0–100:

$$z_j^* = \int_{-\infty}^{\infty} x\mu_j(x)dx \div \int_{-\infty}^{\infty} \mu_j(x)dx$$  (1)

Accordingly, as each risk agent $j$ may be correlated to more than one risk event $i$, the corresponding ARP$_j$ is modeled as the following equation. In this formulation, the larger the APR$_j$ obtained, the higher the risk of the agent is. The fuzzy rules applied are shown as in Table A1:

$$\text{APR}_j = \sum_i z_i^* = \int_{-\infty}^{\infty} x\mu_1(x)dx \div \int_{-\infty}^{\infty} \mu_1(x)dx + \int_{-\infty}^{\infty} x\mu_2(x)dx \div \int_{-\infty}^{\infty} \mu_2(x)dx$$

$$+ \cdots + \int_{-\infty}^{\infty} x\mu_I(x)dx \div \int_{-\infty}^{\infty} \mu_I(x)dx$$  (2)

3.5 Priority for proactive action assignment
Now, following the traditional HOR2 procedure, we prioritize the risk agents according to the APR$_j$ obtained. Then, Pareto analysis can be conducted to identify those highly prioritized risk agents. The proactive actions can be then determined, respectively. It should be noted that one risk agent is possible to be dealt with one or more proactive actions and a single proactive action may be able to mitigate a number of risk agents.

4. Case study—manufacturer in a global supply chain
We conducted a case study for one of the leading manufacturers in small household electrical appliances. This manufacturer produces more than 30m pieces of products annually.
One of its major products is the hair dryer. It has a number of manufacturing plants in Mainland China and customers from all over the world. The suppliers of different materials and components mainly come from East Asia. The company relies on sea freight as the major transportation means for delivering products to overseas customers. This manufacturer is in a very classical large scale global supply chain.

We conducted interviews with 20 staff at the managerial level and 200 operators in different departments of the organization. The data were analyzed and fed into the proposed fuzzy-based HOR for risk analysis. The results are summarized as follows.

### 4.1 Identification and assessment of risk events, risk agents and correlations

Table I shows the risk events identified and the corresponding severity obtained in the plan, source, manufacture, delivery and return aspects. In each process, we further drill down to identify the risk events in each sub-process. Here, we remove those risk events with severity lower than severe to simplify the analysis.

Risk agents were considered as the possible causes of the above risk events identified, and it was assumed that a single risk agent could lead to more than one risk event and one event could be caused by more than one agent. Based on different aspects, including internal, global environment, supplier, customer and third-party logistics, we identified the risk agents and the corresponding occurrences in fuzzy expressions, as summarized in Table II. The correlation between risk events and risk agents are summarized in Table III.

### 4.2 Classifications of the highest risk agents

After the defuzzification, we are able to obtain the ARP for each risk agent and prioritize them from the largest to the smallest, as shown in Figure 6. One can see that there are about ten risk agents which together contributed to 80 percent of the total ARP. Accordingly, these are regarded as high-risk agents (A8, A28, A23, A12, A14, A21, A26, A10, A6 and A27) and

<table>
<thead>
<tr>
<th>Process</th>
<th>Sub-process</th>
<th>Risk events</th>
<th>Severity</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plan</td>
<td>Demand forecasting</td>
<td>Significant error in forecasting</td>
<td>VS</td>
<td>E1</td>
</tr>
<tr>
<td>Requirement planning</td>
<td>Sudden changes in production plans</td>
<td></td>
<td>VS</td>
<td>E2</td>
</tr>
<tr>
<td>Inventory control</td>
<td>Too many outdated goods stored in warehouse</td>
<td>Discrepancy between recorded and available stock</td>
<td>S</td>
<td>E3</td>
</tr>
<tr>
<td>Source</td>
<td>Procurement</td>
<td>Delay in sending purchasing order</td>
<td>S</td>
<td>E5</td>
</tr>
<tr>
<td></td>
<td>Incorrect item sent by supplier</td>
<td></td>
<td>S</td>
<td>E6</td>
</tr>
<tr>
<td></td>
<td>Late delivery</td>
<td></td>
<td>S</td>
<td>E7</td>
</tr>
<tr>
<td>Supplier assessment and relationship management</td>
<td>Sudden loss of key supplier</td>
<td>Supplier go against contract agreement</td>
<td>S</td>
<td>E8</td>
</tr>
<tr>
<td>Manufacture</td>
<td>Production</td>
<td>Insufficient material</td>
<td>S</td>
<td>E10</td>
</tr>
<tr>
<td></td>
<td>Delay in production</td>
<td></td>
<td>S</td>
<td>E11</td>
</tr>
<tr>
<td></td>
<td>Machine breakdown</td>
<td></td>
<td>S</td>
<td>E12</td>
</tr>
<tr>
<td></td>
<td>High scrap rate</td>
<td></td>
<td>S</td>
<td>E13</td>
</tr>
<tr>
<td>Delivery</td>
<td>Packing</td>
<td>Inconsiderate packaging (leak, easy to break, etc.)</td>
<td>S</td>
<td>E14</td>
</tr>
<tr>
<td></td>
<td>Warehousing of final goods</td>
<td>Storage of final goods in distribution center</td>
<td>S</td>
<td>E15</td>
</tr>
<tr>
<td></td>
<td>Delivery of final goods</td>
<td>Late delivery</td>
<td>S</td>
<td>E16</td>
</tr>
<tr>
<td></td>
<td>Incorrect item delivery to customers</td>
<td></td>
<td>S</td>
<td>E17</td>
</tr>
<tr>
<td></td>
<td>Deliver items to wrong destination</td>
<td></td>
<td>S</td>
<td>E18</td>
</tr>
<tr>
<td>Return</td>
<td>Reject from customer</td>
<td>Large amount of rejected items</td>
<td>S</td>
<td>E19</td>
</tr>
<tr>
<td></td>
<td>Delay in handling returns</td>
<td></td>
<td>S</td>
<td>E20</td>
</tr>
<tr>
<td></td>
<td>Return to suppliers</td>
<td>Delay in handing the rejected item to suppliers</td>
<td>S</td>
<td>E21</td>
</tr>
</tbody>
</table>

Table I. Summary of risk events and severity
require the organization to pay special attention. Among these risk agents, A8 was the most significant with APR 700. A8 was an internal factor related to “inaccurate information exchange among departments,” which was related to the information system. This finding was consistent with the discussion of Ruel et al. (2017). In addition, A8 was correlated with many risk events in many different processes, including E1–E5, E10–E11 and E14–E18 with different degrees of correlation. From the results, A28 is rated as the second high-risk agent, which is related to customer “immediate change in demand” and followed by A23, which was related to supplier “poor quality of inward goods/materials from supplier to manufacturer.” In short, modeling of HOR in a fuzzy-based approach can ease the qualitative decision by simply using linguistic words.

5. Conclusions

RM is crucial to any organization, especially to those participating or managing in a global supply chain, which usually face risks coming internally or externally. To manufacturers, internal risks may come from production, labor and information systems, while external risks may come from suppliers, third-party logistics and customers. Based on the problem complexity, this paper applies The SCC Risk Research Team (2008) framework approach to identify systematically the internal and external risk events and risk agents. In order to precisely convert the subjective qualitative decisions of assigning the severity and correlation value between risk events and risk agents, we propose a fuzzy logic expression. To further enhance the modeling accuracy, the occurrence of risk agents is modeled by the

<table>
<thead>
<tr>
<th>Categories</th>
<th>Risk agent</th>
<th>Occurrence</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal</td>
<td>Interrupted electricity supply</td>
<td>L</td>
<td>A1</td>
</tr>
<tr>
<td></td>
<td>Breakdown of IT system</td>
<td>N</td>
<td>A2</td>
</tr>
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numbers of happenings obtained by analyzing the historical data. This fuzzy modeling approach replaces all the subjective value assignments in the traditional HOR approach. We conducted a case study in a leading small electronic home appliance manufacturer, who operates in a classical global supply chain. A total of more than 200 staff were interviewed and collected their view on the risks by the proposed linguistic approach. Our results showed that risk agents can be identified and the corresponding significance can be represented by the modified aggregated potential risk value. With such, it helps the manufacturers to understand better about its risk level and design for the corresponding proactive actions.

In this paper, the risk identification mainly focuses on the manufacturer who is a single component among the global supply chain. More components can be incorporated in the future analysis for risk identification in order to mitigate the supply chain risk. Moreover, regarding data collection, the input data are currently collected form operators or managers. However, as Internet of Things as well as Industry 4.0 are getting more prevalent and mature nowadays, the input data are possible to be collected from different advanced technologies, such as sensors, cloud databases, etc., to improve the efficiency.

References


Sople, V.V. (2012), *Supply Chain Management: Text and Cases*, Dorling Kindersley, Noida.


Further reading


(The Appendix follows overleaf.)
### Table A1.
Fuzzy rules for the fuzzy controller

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<th>Severity</th>
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Using put option contracts in supply chains to manage demand and supply uncertainty

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Abstract

Purpose – The purpose of this paper is to value put option contracts in hedging the risks in a supply chain consisting of a component supplier with random yield and a manufacturer facing stochastic demand for end products.

Design/methodology/approach – This paper adopts stochastic inventory theory, game theory, optimization theory and algorithm and MATLAB numerical simulation to investigate the manufacturer’s ordering and the supplier’s production strategies, and to study the coordination and optimization strategies in the context of random yield and demand.

Findings – The authors find that put options can not only facilitate the manufacturer’s order but also the supplier’s production, that is, the manufacturer and the supplier can effectively manage their involved risks and earn more expected profits by adopting put options. Further, the authors find that the single put option contract fails to coordinate such a supply chain. However, when combined with a protocol, it is able to coordinate the supply chain.

Originality/value – This paper is the first effort to study the intersection of put option contracts and random yield in the presence of a spot market. From a new perspective, the authors explore the supply chain coordination. The authors propose a mechanism to coordinate the supply chain under put option contracts.

Keywords Supply chain management, Demand uncertainty, Put option contracts, Yield uncertainty

Paper type Research paper

Nomenclature

T Random yield rate of the supplier, which is characterized by cumulative distribution function (CDF), probability density function (PDF), $\Phi(t)$ and $\varphi(t)$, respectively.

$E(T) = \mu, T \sim \{(a, b) \mid 0 < a < b \leq 1\}$

D Market demand for the end-product, which is a random variable with CDF $F(x)$ and PDF $f(x)$, and $E(x) = \delta, D \in (0, \infty)$

w Unit wholesale price ($)

o Unit option price of the put option ($)

Unit exercise price of put option ($) $e_p$

Production quantity of the supplier $Q$

Firm order quantity of the manufacturer $q_p^0$

Option order quantity of the manufacturer, $q_p^1 < q_p^0$

Spot market price ($) for the component, which is a random variable with PDF $v$ ($p_s$) and CDF $V(p_s)$ and $E(p_s) = \bar{p}_s, P_s \in [A, B]$

Unit production cost of the component ($) $c$

Unit retail price of the end-product ($) $r$

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1. Introduction

The real option was first designed to amplify fortune or mitigate loss in the capital investment decision making under uncertainty (Lander and Pinches, 1998). Over the last 40 years, the real option has drawn constant attention from scholars in economic field. Different theoretical types of real options have been developed in the early literature, including growth options (Myers, 1977), options to abandon (Bonini, 1977), options to defer (Tourinho, 1979) and scale options (Trigeorgis and Mason, 1987), etc. Meanwhile, various option-type decision-making frameworks have been developed to model and value these real options and derive optimal investment strategies, such as continuous-time models (Black and Scholes, 1973), finite-difference schemes (Brennan and Schwartz, 1978), and trinomial models (Kamrad (1995) and binomial models (Lander and Pinches, 1998). Lander and Pinches (1998) stated that most types of the early models are complex and require substantial mathematical techniques to solve, which are often violated in the application of real options. Later studies endeavor to propose more practical frameworks/models and solutions, for example, the papers of Cassimon et al. (2011), Zhang et al. (2014), Nigro et al. (2014) and Cassimon et al. (2016). Due to its success in investment market, many flexibility contracts derivated from the real option have been widely applied by practitioners and scholars to manage supply chain risks in the last two decades (Barnes-Schuster et al., 2002; Nagali et al., 2008; Chen and Shen, 2012).

Essentially, the real option is a right: by pre-paying a fee, the buyer (manufacturer) gets the right (not the obligation) to reorder items from the seller (supplier) at a predetermined price or the right to return unsold goods to the seller (supplier) at a predetermined salvage value. The former is known as call option contract and the latter put option contract (Burnetas and Ritchken, 2005; Liu et al., 2013). Both option contracts are frequently adopted in practice, e.g., to hedge their risks, Hewlett-Packard Company (Nagali et al., 2008) and China Telecom Corporation Limited (Chen et al., 2014) adopt call option contracts while Enron (Chen and Parlar, 2007) adopts put option contracts. In the academic circle, issues concerning supply chain management with real option contracts have been extensively studied, but the majority of these works focus on the call option contract and a few studies concern about the put option contract (see Nosoohi and Nookabadi, 2016 for a complete review). Furthermore, to the best of our knowledge, there is no research on the application of put option contracts in supply chains in the presence of supply uncertainty so far. Our study accordingly stands on the intersection of put option contracts and supply uncertainty.

Supply uncertainties are not new; they even have existed as long as supply chains (Snyder et al., 2016). In many industries, the problem of unexpected supply disruption (result from man-made or natural disasters such as fires, earthquakes and terrorist attacks, etc.) and yield uncertainty (also known as random yield, due to weather, environment and other unpredictable factors in complicated production) are regarded as the main causes of supply uncertainties (Singhal et al., 2011). In general, disruptions may cause entire or a significant fraction of production loss, but it occurs very infrequently (rare events). In contrast, random yield may cause certain loss of some fraction of production, but it occurs frequently in production and assembly, which will influence the daily production plan. Some industries even suffer from random yield nearly in every batch, e.g. semiconductor, chemicals, agriculture and pharmaceuticals (Kulkarni, 2006; Deo and Corbett, 2009). On the other hand, in literatures, stochastically proportional yield model is commonly adopted to depict yield uncertainty (Yano and Lee, 1995; Grosfeld-Nir and Gerchak, 2004). Under this context, if the yield is a Bernoulli random variable, disruptions can be viewed as a special case of yield uncertainty (Snyder et al., 2016). Hence, we focus on the random yield in this paper. To some extent, we can conclude that our result also makes sense in the case of the disruption.

Motivated by semiconductor industry, this paper considers a one-period two-echelon supply chain composed of one component-supplier and one end-product manufacturer. The production of the supplier is subject to yield uncertainty and the market demand for the end-product is
assumed to be stochastic. The manufacturer contracts the supplier with wholesale price to derive the components and purchase put options to return units after demands have been observed. In addition, there is a spot market on which both the manufacturer and the supplier can buy or sell the components. Several questions can be asked of our model:

1. What is the manufacturer’s optimal ordering policy under put option contracts in the presence of random demand and spot price?
2. What is the supplier’s optimal production policy under put option contracts in the presence of random yield and spot price?
3. How put option contracts impact the optimal policies and profits of the supply chain?
4. Can the channel be coordinated with put option contracts under this context? If not, how can?

The main contributions of this paper are as follows: first, we develop supply chain models incorporating both put option contracts and random yield, and derive the closed-form expression of the supplier’s optimal production policy and the manufacturer’s optimal ordering policy; second, we discuss how put options, variations in cost and price affects optimal decisions and channel performance in supply chain scenarios with random yield and demand; third, from a new perspective, we show that the simple put option contracts fail to coordinate such a complex system. To coordinate the supply chain, we find that a protocol needs to be added to the put option contract; and fourth, we provide explicit conditions on which the supply chain can be coordinated under put option contracts with the protocol. Therefore, our study has made significant contribution to the existing literature.

The paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the notations and model formulation. Section 4 gives a centralized model to be the benchmark case for the decentralized models. Section 5 addresses the manufacturer’s ordering decision and the supplier’s production decision in the decentralized models with put options. Section 6 resorts numerical examples to discuss the impact of put options on the decisions and performances of the supply chain. Section 7 addresses the supply chain coordination. Finally, Section 8 concludes the paper and gives recommendations for future work.

2. Related literature
As suggested in the previous section, issues of randomness involved in production process and real option contracts in supply chain are the essential research topics this paper touches. We provide a brief review of the related literature below. Then, we refer to a tabular to show the position of this work.

2.1 Random yield
Supply chain models with random yield have drawn substantial attention from scholars. Early research mainly focuses on the impacts of random yield on procurement/production strategies under the simple wholesale price contract, such as the papers of Shih (1980), Henig and Gerchak (1990), Inderfurth (2004) and Dada et al. (2007). More detailed review of these research works can refer to Yano and Lee (1995) and Grosfeld-Nir and Gerchak (2004). Later, many researchers have taken great interests in exploring what supply contracts can be used to achieve risk sharing between supply chain members to reduce, even eliminate inefficiencies arising from yield randomness alone or from both stochastic demand and random yield. Among others, Gurnani and Gerchak (2007) introduced a shortage penalty contract to share under-production risk in an assembly system. He and Zhang (2008) proposed a surplus subsidy contract to share over-production risk and investigated how the optimal decisions and performances of the supply chain are affected by it. Li et al. (2013) demonstrated that a supplier
and a buyer can be coordinated by an accept-all shortage penalty contract. Hu et al. (2013) found that compared with the single decision parameter, the min and max double parameters can significantly improve the performance of a two-echelon supply chain, but it cannot coordinate the system unless it is combined with revenue sharing and Order penalty and rebate strategies. Luo and Chen (2016) pointed out that the traditional revenue sharing contract, combined with a surplus subsidy mechanism, can coordinate a random yield supply chain and allow the system profit to be divided between members arbitrarily. Giri et al. (2016) showed that a composite contract combining sales rebate and penalty contracts and buyback can coordinate a three-layer supply chain. The previous researchers do not consider real option contracts.

2.2 Real option contracts
As stated in the introduction, literatures on adopting real option contracts to increase operational flexibility and manage supply chain risks can be classified into two categories: call option contracts and put option contracts. To highlight our contributions, only the most relevant literatures have been reviewed in this paper.

2.2.1 Call option contracts. There is a rich body of literature on supply chain management with call option contracts. Those literatures can be divided into two categories. One category concentrated on the procurement or/and pricing policy under different situations. Examples include the case with competition (Wu and Kleindorfer, 2005), capacity constraints (Xu, 2006), capital constraint (Feng et al., 2014) and customer returns (Wang et al., 2017). Another category focused on the issue of supply chain coordination, such as Barnes-Schuster et al. (2002), Wang and Liu (2007), Zhao et al. (2010), Chen et al. (2014) and Nosoohi and Nookabadi (2014). In particular, some researcher jointed real option contracts with other mechanism to coordinate a supply chain, for example, Arani et al. (2016) introduced a European call option with a revenue-sharing mechanism to coordinate a retailer-manufacturer supply chain. It is worth noting that all the research works mentioned above only consider the demand to be random.

There are some researchers concerning the real option contracts under random yield and demand, for example, Xu (2010) studied the impacts of real option contracts on the optimal decision (procurement and production) and the expected profit of a supplier-manufacturer supply chain. Considering a manufacturer can order components through a wholesale price contract from an unreliable supplier while through real option contracts from an additional reliable supplier, Kaki et al. (2014) developed a scenario-based framework to study optimal procurement strategy of the manufacturer. Cai et al. (2017) introduced an option contract with subsidy contract to coordinate a vendor-managed inventory supply chain. Our study is different from the above papers in that we focus on the put option contract, while they considered call option contracts.

2.2.2 Put option contracts. Currently, adopting put option contracts to manage supply chain risks gain an increasing prevalence among researchers. Burnetas and Ritchken (2005) investigated how the wholesale price and strike price adjust after the introduction of put option contracts under a downward sloping demand curve. Chen and Parlar (2007) studied the effects of a put option for a risk-averse newsvendor’s decision and profits. Considering capacity and order constraints, Liu et al. (2013) examined the value of put option contracts in a two-echelon container shipping service chain. In addition, Nosoohi and Nookabadi (2016) investigated the outsourcing model with put options in the case that both demands and costs are uncertainty. Wan and Chen (2017) studied the role of put option contracts in hedging the risks of price and demand caused by inflation in a retailer – supplier supply chain. These papers above study multiple uncertainty factors in a decentralized supply chain but exclude the supply uncertainty, especially, the random yield.

In order to better understand our contributions to the above-mentioned fields, we refer to a tabular to show the position of this work (see Table I), which focuses on put option in supply chain in the presence of random yield risk.
### 3. Model formulation
The sequence of events goes as follows:

1. The supplier declares unit wholesale price $w$, option price $o$ and exercise price $e_p$ of the components.

2. Knowing $w$, $o$ and $e_p$, the manufacturer places firm order $q^0_p$ and put option order $q^1_p$ units of the components.

3. Based on $q^0_p$ and $q^1_p$, the supplier decides his optimal production quantity $Q_p$ of the components.

4. The actual output of the components supplier is $tQ_p$, $t$ is the realized value of the random variable $T$. If $tQ_p < q^0_p$, then the supplier buys the shortage $(tQ_p - q^0_p)$ units from the spot market at random price $p_s$ to fulfill the contacts, otherwise, the supply sells the residual components $(q^0_p - tQ_p)$ units on the spot market at a reduced price $\alpha p_s$.

5. The manufacturer receives the exact quantity he ordered initially.

6. The products demand is realized ($x$). If $x \geq q^0_p$, the manufacturer buys $(x - q^0_p)$ units from the spot market at random price $p_s$ to meet end-users and never exercises the put options, otherwise, the manufacturer exercises the put options and sells the excess amount $(q^0_p - x)$ on the spot market at price $\alpha p_s$.

It should be noted that the component is bought and sold on the spot market at a different price since the spot market is usually short for liquidity or perfect market access, which has been acknowledged as a major killer for public B2B exchanges (Wu and Kleindorfer, 2005; Mendelson and Tunca, 2007; Luo and Chen, 2017). Like Luo and Chen (2017), we adopt $\alpha$ to refer to the probability that sellers can find a last-minute buyer or the percentage of the total amount that can be sold on the spot market when the realized spot price is $p_s$. In addition, we assume that when the manufacturer exercises the put options, the components need not be returned to the supplier and the manufacturer will get cash compensation from the supplier. For the components, they will be sold on the spot market. The compensation price for the put option is assumed $(e_p - \alpha p_s)^{+}$, that is, when $e_p > \alpha p_s$, the supplier compensates the manufacturer at the price $(e_p - \alpha p_s)$ for $\min[(q^0_p - x), q^1_p]$ units of components; when $e_p \leq \alpha p_s$, the supplier does not give any compensation to the manufacturer.

The description above reveals that $r > \bar{p}_s > w > c/\mu > \alpha \bar{p}_s$, otherwise the manufacturer and the supplier would not produce anything, and $w > e_p - o > \alpha \bar{p}_s$, otherwise the manufacturer will never place firm order and put option order from the supplier. The manufacturer and the supplier are risk neutral, rational and information symmetry.

### 4. Centralized model—the benchmark case
To obtain a benchmark for decentralized models, we first consider the centralized case where the manufacturer and the supplier are assumed to belong to the same company.

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<th>Random yield</th>
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### Table I
Summary of the most related literature
Let $Q^l$ denote the centralized supply chain’s decision on how many products (components) to produce, then the expected profit of the centralized system is:

$$\Pi_l(Q^l) = rED + \alpha p_s E\left(TQ^l - D\right)^+ - cQ - \bar{p}_s E\left(D - TQ^l\right)^+.$$  

(1)

The first two terms refer to the sales revenues from selling the end product to end-users and selling the residual components on the spot market, respectively. The last two terms are the costs of normal production and purchasing components on the spot market, respectively.

Therefore, the optimal components production problem of the supply chain can be characterized in the following lemma:

Lemma 1. $\Pi_l(Q^l)$ is concave in $Q^l$, and $Q^*$ satisfies:

$$\int_0^1 F(tQ^*)t\varphi(t)dt = \frac{\bar{p}_s \mu - c}{(1 - z)p_s}.$$  

(2)

Lemma 1 means that under yield randomness and demand uncertainty in the presence of a spot market, the supply chain’s optimal components production quantity exists and is unique, and it is increasing in the mean value of the spot price $\bar{p}_s$, the risk factor $\alpha$ and decreasing in the production cost $c$.

5. Decentralized models with put options

In the decentralized case, the manufacturer and the supplier are primarily concerned with optimizing their own objectives. In this section, we develop models to derive and analyze the manufacturer’s optimal ordering policy and the supplier’s optimal production policy with put options.

5.1 Manufacturer’s optimal ordering policy

According to the description above, the manufacturer’s decision variables are: the firm order quantity $q^0_p$, the put option order quantity $q^1_p$. Therefore, when $e_p \leq \alpha p_s$, the expected profit of the manufacturer is:

$$\pi^m_p(q^0_p, q^1_p) = rED - wq^0_p - oq^1_p - \bar{p}_s E\left(D - q^0_p\right)^+ + \alpha p_s E\left(q^0_p - D\right)^+.$$  

(3)

The first term on the right side of Equation (3) is the revenues earned by selling the finished products. The next two terms are the costs associated with firm order and put option order, respectively. The fourth term is the cost of spot purchasing and the last one is the revenue earned by dealing with the residual components on the spot market. When $e_p > \alpha p_s$, the expected profit of the manufacturer is:

$$\pi^m_p(q^0_p, q^1_p) = rED - wq^0_p - oq^1_p + (e_p - \alpha p_s)E\min\left[\left(q^0_p - D\right)^+, q^1_p\right]$$

$$- \bar{p}_s E\left(D - q^0_p\right)^+ + \alpha p_s E\left(q^0_p - D\right)^+.$$  

(4)

The fourth term on the right side of Equation (4) refers to the compensation offered by the supplier when the manufacturer exercises the options; other terms are all the same as that of Equation (3).
Let $\int_{p_\min}^{p_\max} p \, dp = \bar{p}$ and $\int_{p_\min}^{p_\max} q \, dp = \bar{q}$, we have:

$$\pi_p^m(q_p^0, q_p^1) = rED - wq_p^0 - oq_p^1 + (e_p V(\frac{e_p}{\alpha}) - \alpha p)E \min \left( q_p^0 - D, q_p^1 \right)$$

$$-\bar{p}, E \left( D - q_p^0 \right) + \alpha \bar{p}, E \left( q_p^0 - D \right) + \bar{q}.$$

(5)

**Lemma 2.** When $\bar{p} - \alpha p > e_p V(\frac{e_p}{\alpha}) > \alpha p$, $\pi_p^m(q_p^0, q_p^1)$ is concave in $(q_p^0, q_p^1)$ and $q_p^{0*}$ and $q_p^{1*}$ are satisfy:

$$\begin{cases} q_p^{0*} = F^{-1}(C) \\ q_p^{1*} = F^{-1}(C) - F^{-1}(D) \end{cases}$$

(6)

where:

$$C = \frac{\bar{p} - w - o}{(1 - \alpha p)} - e_p V(\frac{e_p}{\alpha}) + \alpha p, \quad D = \frac{e_p V(\frac{e_p}{\alpha}) - \alpha p}{(1 - \alpha p)}.$$

Lemma 2 indicates that when the put option contracts are adopted, the manufacturer’s optimal firm order quantity $q_p^{0*}$ and optimal option order quantity $q_p^{1*}$ are determined by the distributions of market demand $F(x)$ and spot price $V(p)$, the wholesale price $w$, the ordering price of put options $o_p$ and the exercising price $e_p$ and the discount rate of spot price $\alpha$.

**P1.** $q_p^{0*}$ and $q_p^{1*}$ are decreasing in $(w, o)$ and increasing in $e_p$.

**P1** suggests that the increase of the wholesale price and the option price will lower the manufacturer’s firm order quantity and put option order quantity. In contrast, the increase of the exercising price will increase the manufacturer’s firm order quantity and put option order quantity. This is because when put options are adopted, the manufacturer can get the return flexibility through purchasing put options so as to reduce the risk caused by demand randomness. However, when the wholesale price is high, the manufacturer’s firm orders purchasing cost or the order cost of put options for each component will increase too. Facing a highly uncertain market demand, the manufacturer prefers to take the possible loss caused by the random spot price instead of the possible loss caused by the high contract purchasing cost, that is, the manufacturer will increase its spot purchase while decrease its contract purchase. When the exercising price is high, the compensation the manufacturer obtains when it exercises put options is high, too, which surely encourages the manufacturer to increase its purchasing quantity of put options to reinforce its return flexibility and at the same time increase its firm order so as to offset the high uncertainty of demand and spot price. Under such circumstances, the manufacturer will increase its contract purchase while reduce the spot purchase.

### 5.2 Supplier’s optimal production policy

With put option contracts, for the given manufacturer’s order pair $(q_p^{0*}, q_p^{1*})$, the supplier’s problem is to determine the components production quantity $Q_p$ to maximize its expected profit $\pi_s^*(Q_p)$. When $\alpha p < e_p$, the expected profit of the supplier is:

$$\pi_s^*(Q_p) = wq_p^{0*} + oq_p^{1*} + \alpha p, E \left\{ TQ_p - q_p^{0*} \right\}^+ - cQ_p - p, E \left\{ q_p^{0*} - TQ_p \right\}^+.$$

(7)

The first two terms on the right side of Equation (7) are the revenues earned by selling the firm order and put options ordered to the manufacturer, respectively. The third one is the
revenues earned by selling residual units (if any) to the spot market. The last two terms are 
costs associated with the production of the components and the purchase of the shortfall 
from the spot market.

When \( \alpha p_s < e_p \), the expected profit of the supplier is:

\[
\pi_p^s(Q_p) = w q_p^{0*} + o q_p^{1*} - (e_p - x p_s) E \left[ \left( q_p^{0*} - D \right)^+, q_p^{1*} \right] 
+ x p_s E \left\{ T Q_p - q_p^{0*} \right\}^+ - c Q_p - p_s E \left\{ q_p^{0*} - T Q_p \right\}^+. 
\] (8)

The third term on the right side of Equation (8) is the compensation the supplier should give 
to the manufacturer who exercises put options. Other terms refer to the same things as that 
of Equation (7).

Since \( \int_{A/2}^0 p_s v(p_s) dp_s = \rho_p \) and \( \int_{e_p/2}^B p_s v(p_s) dp_s = \overline{\rho}_p \), we get:

\[
\pi_p^s(Q_p) = w q_p^{0*} + o q_p^{1*} - (e_p V(e_p/\alpha) - x p_s) E \left[ \left( q_p^{0*} - D \right)^+, q_p^{1*} \right] 
+ x \overline{p}_s E \left\{ T Q_p - q_p^{0*} \right\}^+ - \overline{\rho}_s E \left\{ q_p^{0*} - T Q_p \right\}^+ - c Q_p. 
\] (9)

Lemma 3. \( \pi_p^s(Q_p) \) is concave in \( Q_p \), \( Q_p^* \) is satisfies:

\[
\int_{q_p^{0*}}^{q_p^{1*}} t \varphi(t) dt = \frac{c - x \overline{p}_s \mu}{(1-\alpha) \overline{\rho}_s}. 
\] (10)

Lemma 3 indicates that the optimal production input \( Q_p^* \) of the supplier with put options is 
determined by the manufacturer’s optimal firm order quantity \( Q_p^{0*} \), the distribution of 
production output rate \( \varphi(t) \), the production cost \( c \), the average spot price \( \overline{p}_s \) and the discount 
rate of spot price \( \alpha \).

Further, Equation (10) shows that the optimal production input of the supplier increases 
with the increase of the manufacturer’s optimal order quantity, the average spot price and 
the discount rate, while decreases with the increase of the production cost. Conversely, the opposite is true. This is easy to understand because the more the manufacturer orders, the more profit the supplier can get, which surely will encourage the supplier to increase its production input. When the average spot price or the discount rate is high, the cost for the spot purchase is high and the revenue from selling the residual components on the spot market is also high. The supplier of course will increase its production input and reduce its spot purchase. In contrast, when the production cost is high, the supplier prefers to take the possible loss caused by the random spot price rather than the loss caused by high production cost and stochastic yield, that is, the supplier will increase its spot purchase while reduce its production input.

6. Effect of put options

Lemma 2 and Lemma 3 suggest that there is a unique Nash equilibrium between the order 
quantity of the manufacturer and the production input of the supplier under the 
decentralized system with put options. Based on the research findings, in this section, we 
will investigate the effect of put options on the decision making and profit of supply chain management by comparing with the case of without put options.
Let $q^*_o$ be 0 in Equation (5) and $q^*_p$ be 0 in Equation (9), we can get that the optimal order quantity of the manufacturer in the case of without put options, denoted by $q^*$, is $q^* = F^{-1}((\bar{p}_s-w)/(1-\alpha))$, and the optimal production quantity of the supplier, denoted by $Q^*$, is determined by $\int_0^\infty e^{Q^*} t_0(t)dt = (c-2\bar{p}_s\mu)/(1-\alpha)$.

Here, we resort to numerical experiments to reach this goal. In our experimental setting, the combination of yield rate, demand and spot price distributions are assumed as {Uniform, Normal and Uniform}. Throughout this numerical study, we consider a base case where the exercise prices are assumed as $r = \frac{1}{2}$.

For the order quantity of the manufacturer in the case of without put options, denoted by $Q^*$, we can get the optimal order quantity $Q^*$ as $10$, $20$, $30$ and $40$ for different exercise prices $r = \frac{1}{2}$, $\frac{1}{3}$, $\frac{1}{4}$ and $\frac{1}{5}$, respectively; fix the option price $\frac{1}{2}$, $\frac{1}{3}$, $\frac{1}{4}$ and $\frac{1}{5}$, respectively; and fix the exercise price $\frac{1}{2}$, $\frac{1}{3}$, $\frac{1}{4}$ and $\frac{1}{5}$, respectively.

The values of $Q^*$, $\pi^s(q^*)$, $\pi^m(q^*)$, $\pi^s(\pi^m(q^*))$, $\pi^m(\pi^s(q^*))$ and $\pi^s(\pi^m(q^*))$ are $387.5$, $388.5$, $389.5$, $390.5$, $391.5$ and $392.5$, respectively. Note that in these figures, the solid line and the dotted line stand for the cases of with and without options, respectively.

Figure 1 shows that as the exercise price increases, the firm order quantity, the option quantity and the expected profit of the manufacturer as well as the production quantity of the supplier decreases, while the expected profit of supplier first increases then decreases. This is due to the fact that the higher option price means a higher purchasing cost for the put option, which may induce the manufacturer to place less firm orders and put option orders and obtain less flexibility to respond to its risks. For the supplier, the decrease of the total order quantity will eventually decrease the growth of its production, the initial increase in the option price may lead to the increase in the profit, but it will be bad for the supplier if the option price is too high.

Figure 2 shows that as the exercise price increases, the firm order quantity, the option quantity and the expected profit of the manufacturer as well as the production quantity of the supplier decrease, while the expected profit of supplier decreases, and the production quantity of the manufacturer decreases. This is due to the fact that the higher option price means a higher purchasing cost for the put option, which may induce the manufacturer to place less firm orders and put option orders and obtain less flexibility to respond to its risks. For the supplier, the decrease of the total order quantity will eventually decrease the growth of its production, the initial increase in the option price may lead to the increase in the profit, but it will be bad for the supplier if the option price is too high.

<table>
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<th>$\pi^m(q^*)$</th>
<th>$\pi^s(\pi^m(q^*))$</th>
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Figure 1. Optimal decisions and expected profits under different option prices

Figure 2. Optimal decisions and expected profits under different exercise prices
the supplier increases, while the expected profit of supplier first increases, then decreases.
This is due to the fact that the higher exercise price implies a higher compensation the
manufacturer may receive from the supplier, which entices the manufacturer to purchase
more put options and obtain more flexibility to respond to its risks. For the supplier, the
increase of the total order quantity will promote the growth of its production, which leads to
the increase of profits when the exercise price is not very high, but it is bad for the supplier
when the exercise price exceeds a certain value.

Observing the figures above, we have the following remark:

Remark 1. With random yield, demand and spot price, under some contract parameter
settings, the manufacturer’s optimal firm order quantity and the supplier’s
optimal production quantity as well as both parties’ expected profit with put
options are higher than that of without.

This remark implies that with put options, the manufacturer and the supplier can effectively
manage their involved risks and earn more expected profits than without. That is, both firms
can benefit from put option contracts in the case of demand uncertainty and random yield.

Next, we compare the optimal decisions and expected profits under the variabilities of
yield, demand and spot price. We fix the mean demand δ = 100, let the standard deviation be
10, 20, 30 and 40, respectively; fix the mean yield rate μ = 0.5, let the standard deviation be
the values of 0.25, 0.3, 0.35 and 0.4; fix the mean spot price $p_s = 6.5$, let the standard
deviation be 1.9, 2.1, 2.3 and 2.5. The results are summarized in Figures 3–5.

Figure 3 shows that the manufacturer’s optimal order and expected profit will not change
with the fluctuation of the variance of yield rate, whereas, both the optimal production and the
expected profit of the supplier decreases as the yield variability increases under both cases
(with or without options). Although the supplier’s expected profit with put options is also
higher than without, the increment decreases as the yield variability increases. The reason lies
in that under forced contracts compliance, the firm order can be fully satisfied whatever the

![Figure 3.](image1.png)
Optimal decisions and expected profits under yield variability

![Figure 4.](image2.png)
Optimal decisions and expected profits under demand variability
supplier’s actual output is, so the manufacturer’s decision and profit are not affected by the yield uncertainty. For the supplier, high yield variability means high under-production or over-production risks, so it will reduce the production level and turn to the spot market to fulfill the contract. In a word, the yield randomness has no influence on the manufacturer under forced contract compliance, but it is bad for the supplier.

From Figure 4, it can be seen that as the demand variability increases, the manufacturer’s optimal firm order and the supplier’s optimal production quantity decreases under the two cases, while the optimal option order increases. It is consistent with the intuition that the higher the demand variability, the lower firm order and the higher option order the manufacture will place, which eventually leads to the decrease in the production quantity of the supplier. Moreover, we find that the profit increment of (the expected profit with put options minus the case of without) the two firms increases as the demand variability increases. It can be concluded that put options are more valuable when the demands are more volatile.

Figure 5 shows that without put options, the decision and the expected profit of both firms will not change with the fluctuation of the variance of spot price; in contrast, when put options are adopted, as the yield variability increases, the firm order, the option order and the production increases. It is consistent with the intuition that high variation of the spot price will urge the manufacturer to purchase more contracts while reduce spot market purchase. Moreover, from Figure 5, we find that as the spot price variability increases, the expected profit of the manufacturer increases and the expected profit of the supplier first decreases and then increases at a slow pace. Simultaneously, the profit increment derived from put options for the manufacturer also increases as the spot price variability increases, and for the supplier, it first increases and then decreases. Noteworthy, it can be found that when the spot price variability is small, both the manufacturer and the supplier are worse with put options than without, only when the spot price variability reaches a certain level, the two firms will benefit from the put option. However, if the spot price variability is too high, adopting put option is bad for the supplier.

In a word, these figures above fully demonstrate that the put options can not only facilitate the manufacturer’s order but also the supplier’s production in a decentralized setting. In other words, with put options, the double marginalization effect will be diminished and the performance of the entire supply chain will be improved. Here comes an interesting question, whether the double marginalization effect can be completely eliminated, that is, whether the supply chain can be coordinated with put options.

7. Supply chain coordination

Now we discuss the supply chain coordination. In this section, we focus on two questions: Can the supply chain with random yield and stochastic demand in the presence of a spot market be coordinated under put option contracts? If not, how can the supply chain coordination be achieved?
Let $\Pi(q^*_0, q^*_1, Q^*_p)$ be defined as the expected profit of the decentralized setting under put contracts. Then

$$\Pi(q^*_0, q^*_1, Q^*_p) = \pi^m(q^*_0, q^*_1) + \pi^d(Q^*_p)$$

$$= rED + \bar{p}s \left\{ T Q^*_p - q^*_0 - \min \left[ (D - q^*_0)^+, q^*_1 \right] \right\}^+ + \bar{p}s \left( q^*_0 - D \right)^+$$

$$- \bar{p}s \left\{ q^*_0 + \min \left[ (D - q^*_0)^+, q^*_1 \right] - T Q^*_p \right\}^+ - \bar{p}s \left( D - q^*_0 - q^*_1 \right)^+ - c Q^*_p.$$

The nature of coordination is to drive the members to make decision in the best interest of themselves as well as the supply chain so as to achieve optimal performance (Cachon, 2003). In other words, once a supply chain is coordinated, it means that not only the optimal policy but also the total maximum expected profit of the decentralized setting will be aligned with that of the centralized. Hence, we compare the maximum expected profit of the supply chain under the decentralized with the centralized setting by assuming that the supplier’s production quantity is $Q^*_p = Q^*_I$. The results are as follows:

1. If $tQ^*_I < q^*_0$, then:
   - When $tQ^*_I < q^*_0 < x$, $\Pi(q^*_0, q^*_1, Q^*_I) = rx - \bar{p}s(x - tQ^*_I) - cQ^*_I = \Pi'(Q^*_I)$;
   - When $tQ^*_I < x < q^*_0$, then:
     $$\Pi(q^*_0, q^*_1, Q^*_I) = rx - \bar{p}s(q^*_0 - tQ^*_I) + \bar{p}s(q^*_0 - x) - cQ^*_I$$
     $$< rx - \bar{p}s(q^*_0 - tQ^*_I) + \bar{p}s(q^*_0 - x) - cQ^*_I$$
     $$= rx - \bar{p}s(x - tQ^*_I) - cQ^*_I = \Pi'(Q^*_I);$$
   - When $x < tQ^*_I < q^*_0$, then:
     $$\Pi(q^*_0, q^*_1, Q^*_I) = rx - \bar{p}s(q^*_0 - tQ^*_I) + \bar{p}s(q^*_0 - x) - cQ^*_I$$
     $$< rx - \bar{p}s(q^*_0 - tQ^*_I) + \bar{p}s(q^*_0 - x) - cQ^*_I$$
     $$= rx + \bar{p}s(tQ^*_I - x) - cQ^*_I = \Pi'(Q^*_I).$$

2. If $tQ^*_I > q^*_0$, then:
   - When $tQ^*_I > q^*_0 > x$, then:
     $$\Pi(q^*_0, q^*_1, Q^*_I) = rx + \bar{p}s(tQ^*_I - x) - cQ^*_I = \Pi'(Q^*_I);$$
   - When $tQ^*_I > x > q^*_0$, then:
     $$\Pi(q^*_0, q^*_1, Q^*_I) = rx - \bar{p}s(x - q^*_0) + \bar{p}s(tQ^*_I - q^*_0) - cQ^*_I$$
     $$< rx - \bar{p}s(x - q^*_0) + \bar{p}s(tQ^*_I - q^*_0) - cQ^*_I$$
     $$= rx + \bar{p}s(tQ^*_I - x) - cQ^*_I = \Pi'(Q^*_I);$$
From the analysis above, we can see that the maximum expected profit of the decentralized setting $\Pi(q^0_p, q^1_p, Q^*)$ is lower than that of the centralized setting $\Pi^c(Q^*)$ in the case of $tQ^* < x < q^0_p$, $x < tQ^* < q^0_p$, $tQ^* > x > q^0_p$ and $x > tQ^* > q^0_p$, which reveals that under put option contracts, the decentralized supply chain cannot be coordinated and the supplier is unlikely to set $Q^*$ as its optimal production.

The reasons accounting for the phenomenon are as follows. When, $tQ^* < x < q^0_p$ and $x < tQ^* < q^0_p$, the supplier must buy the gap $(q^0_p - tQ^*)$ on the spot market to deliver the firm order quantity $q^0_p$ to the manufacturer, while the manufacturer has to deal with the redundancy on the spot market. The different transaction costs resulting from the imperfect access to the spot market between buying and selling the components on the spot market finally result in revenue loss to the decentralized supply chain. Similarly, when $tQ^* > x > q^0_p$ and $x > tQ^* > q^0_p$, the supplier has to deal with the surplus parts while the manufacturer buys its unmet demands on the spot market, it also results in revenue loss for the whole system.

To avoid the problem above, we find that a protocol needs to be added to the put contracts, i.e. if both the realized demand and the supplier’s actual output are less than the manufacturer’s firm order quantity, the quantity the supplier needs to deliver to the manufacturer is the maximum of the realized demand and the actual output; if both the realized demand and the supplier’s actual output are more than the manufacturer’s firm order quantity, the manufacturer must replenish its unmet demands from the supplier first and then on the spot market. Combine put option contracts with the additional protocol, use $\tilde{q}^0_p$ to denote order quantity and use $\tilde{q}^1_p$ to denote production quantity, we can express the supplier’s and the manufacturer’s expected profit as follows:

\[
\begin{align*}
\pi^v_p(\tilde{q}^0_p, \tilde{q}^1_p) &= rED - w \max \left[ \min \left( \tilde{q}^0_p, D \right), \min \left( \tilde{q}^0_p, T\tilde{Q}_p \right) \right] - o\tilde{q}^1_p \\
&\quad + \left( eV(e/x) - \alpha_p \right) E \min \left[ \max \left( \min \left( \tilde{q}^0_p, D \right), \min \left( \tilde{q}^0_p, T\tilde{Q}_p \right) \right) - D \right]^+, \tilde{q}^1_p \\
&\quad - \bar{p}_s E \left( D - \tilde{q}^0_p \right)^+ + \bar{p}_s \min \left( \left( \tilde{q}^0_p - D \right)^+, \left( T\tilde{Q}_p - D \right)^+ \right). \\
\end{align*}
\]

\[
\begin{align*}
\pi^v_p(\tilde{Q}_p) &= w \max \left[ \min \left( \tilde{q}^0_p, D \right), \min \left( \tilde{q}^0_p, T\tilde{Q}_p \right) \right] + o\tilde{q}^1_p \\
&\quad - \left( e_p V(e_p/x) - \alpha_p \right) E \min \left[ \max \left( \min \left( \tilde{q}^0_p, D \right), \min \left( \tilde{q}^0_p, T\tilde{Q}_p \right) \right) - D \right]^+, \tilde{q}^1_p \\
&\quad + \bar{p}_s \min \left( \left( D - \tilde{q}^0_p \right)^+, \left( T\tilde{Q}_p - \tilde{q}^0_p \right)^+ \right) + \bar{p}_s E \left( T\tilde{Q}_p - \tilde{q}^0_p \right) \\
&\quad - \min \left[ \left( D - \tilde{q}^0_p \right)^+, \left( \tilde{Q}_p - \tilde{q}^0_p \right)^+ \right] + \bar{p}_s E \min \left\{ \left( \tilde{q}^0_p - T\tilde{Q}_p \right)^+, \left( D - T\tilde{Q}_p \right)^+ \right\} - c\tilde{Q}_p.
\end{align*}
\]
We can see that $\Pi_p(q_{0p}^*, q_{1p}^*, \hat{Q}_p) = \pi_p^m(q_{0p}^*, q_{1p}^*) + \pi_p^s(\hat{Q}_p) = \Pi'(\hat{Q}_p)$ for any $\hat{Q}_p$, which implies that the supplier’s objective becomes aligned with the supply chain’s objective and the decentralized supply chain can be coordinated under put option contracts with the protocol. Further, from Equation (12), we have the following Lemma:

Lemma 4. $\pi_p^s(\hat{Q}_p)$ is concave in $\hat{Q}_p$, and $\hat{Q}_p$ is given by:

$$\hat{Q}_p = \frac{1}{C_0} \left( \int_0^1 F(t\hat{Q}_p^*) t \varphi(t) dt - (w - z\overline{p} - e_p V(e_p/\alpha)) \right) \int_0^\hat{Q}_p F(t\hat{Q}_p^*) t \varphi(t) dt = \left( \overline{p}, \mu - c \right).$$ (13)

Next, we explore the condition on which the supply chain can be coordinated under put option contracts with the protocol. To coordinate the channel and achieve the optimal expected profit of the system, the supplier should provide $w, o, e_p$ to push it produce just $Q^{I*}$. Hence, we derive the following result:

$P2.$ Under put option contracts with the additional protocol, the decentralized supply chain can be coordinated when system parameters satisfy:

$$w = z\overline{p} + e_p V(e_p/\alpha).$$ (14)

It can be noted that the coordination condition is related to the wholesale price $w$ and the exercise price $e_p$ but not related to the option price $o$, which reveals that $o$ does not influence the total system profits. From Equation (14), it is obvious that $o$ can be adopted to control the allocation of system profit between the manufacturer and the supplier. Compared with the non-coordinating scenario, there are sufficient coordination contracts to achieve a win-win situation.

8. Conclusions and future research

The paper studies on the application of put option contracts in supply chains where the supplier is subject to random yield and the manufacturer faces a stochastic market demand in the presence of a spot market. We take into consideration that both the manufacturer and the supplier can buy or sell the components on the spot market. Table I shows that this is the first study to apply put option contracts in supply chain management with random yield. By developing supply chain models incorporating put option contracts and random yield, we derive several management insights as follows:

(1) Under put option contracts, there exist unique optimal ordering policy (firm and option order) for the manufacturer and unique optimal production policy for the supplier when both yield and demand are random in the presence of a spot market. In addition, the closed-form expressions of those policies show that the firm order quantity and put option order quantity are decreasing in the wholesale price and the option price, while increasing in the exercising price. For the optimal production quantity, it increases with the average spot price and the discount rate, while decreases with the increase of the production cost. This finding provides useful insights into the decision making of the manufacturer’s ordering and the supplier’s production and the setting of the contract parameters.

(2) In comparison with the case of without put option, we find that put options can not only facilitate the manufacturer’s order but also the supplier’s production in a decentralized setting, that is, with put options, the manufacturer and the supplier can effectively manage their involved risks and earn more expected profits than without, and the performance of the entire supply chain will be improved. This finding offers significant insights into the selection of contracts in supply chain management when there are demand risk and supply uncertainty risk.
We also show that the single put option contract cannot achieve the channel coordination; however, when combined with a protocol, it is able to coordinate the supply chain. Further, we identify conditions on which supply chains can be coordinated under put option contracts with the protocol. More importantly, the proposed contract is flexible enough to achieve a win-win situation for the manufacturer and the supplier. This observation sheds new light on developing coordination mechanism to improve the profit of all supply chain parties.

Like any other models proposed in the literature, our model also has some limitations. For example, we adopt a stochastically proportional yield model (also called multiplicative yield model) to depict the yield risk, which has been frequently used in the literatures (Yano and Lee, 1995; Grosfeld-Nir and Gerchak, 2004). Nevertheless, this model is more applicable to such industries as semiconductor and pharmaceuticals. As for the agriculture-related industries, the additive yield model may be more suitable, that is, for an input $Q$ of the supplier, the actual output is $Q + T(T \in [a, b]; -Q \leq a \leq 0, b \geq 0)$ (see Keren, 2009). Therefore, one direct extension of this work is to incorporate additive models to make our study more practical and applicable in a wider range of industries. Second, in this paper the spot price ($p_s$) is assumed random but independent from demand and yield, although such setting simplifies the modeling and provides some interesting insights, we have to acknowledge that the spot price is often dependent on the yield and demand. One key research direction is to consider the spot price to be correlated with the yield or/and demand. Third, our paper assumes that all cost and profit parameters are exogenous so as to focus on how put options affect the supplier’s production decision making and the manufacturer’s ordering decision making as well as each party’s performance. Hence, one possible extension of this work is to set the contract parameters as well. Besides, our model can also expand to include such scenarios as information asymmetry, loss-averse decision makers and multi-suppliers and/or multi-manufacturers. In all, this study offers significant insights for both practitioners and researchers.

References


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Appendix

Proof of Lemma 1. Equation (1) can be further rewritten as:

\[ \Pi'(Q') = (r - \bar{\mu}) - (1 - \alpha) \bar{\mu} \int_0^{t Q'} F(x) \Phi(t) dx + \left( \bar{\mu} - c \right) Q'. \]

Then, \((d\Pi'(Q'))/dQ' = -(1 - \alpha) \bar{\mu} \int_0^{t Q'} F(tQ') \Phi(t) dt + (\bar{\mu} - c)\]
and:

\[ \frac{d^2 \Pi'(Q')}{dQ'^2} = -(1 - \alpha) \bar{\mu} \int_0^{t Q'} F(tQ') \Phi(t) dt < 0. \]

It follows from formulas above that \(\Pi'(Q')\) is strictly concave in \(Q'\), and a unique components production quantity \(Q'^*\) which maximizes \(\Pi'(Q')\) exists. By the first-order optimality condition, we can get Equation (2).

Proof of Lemma 2. Equation (5) can be further rewritten as:

\[ \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p}) = \left( r - \bar{\mu} \right) - (1 - \alpha) \bar{\mu} \int_0^{q^{0}_{p} - q^{1}_{p}} \left( e_p V(e_p / z) - z \right) dx \]

It shows that:

\[ \frac{\partial \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial q^{0}_{p}} = \left( \bar{\mu} - w \right) - (1 - \alpha) \bar{\mu} \int_0^{q^{0}_{p} - q^{1}_{p}} F(q^{0}_{p}) dx \]

and:

\[ \frac{\partial^2 \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial (q^{0}_{p})^2} = \left[ (1 - \alpha) \bar{\mu} - e_p V(e_p / z) + z \right] f(q^{0}_{p}) \]

and:

\[ \frac{\partial^2 \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial q^{0}_{p} \partial q^{1}_{p}} = \frac{\partial^2 \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial (q^{1}_{p})^2} = - \left( e_p V(e_p / z) - z \right) f(q^{0}_{p} - q^{1}_{p}) \]

and:

\[ \frac{\partial^2 \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial q^{0}_{p} \partial q^{1}_{p}} = \frac{\partial^2 \pi_{p}^{m}(q^{0}_{p}, q^{1}_{p})}{\partial q^{1}_{p} \partial q^{0}_{p}} = \left( e_p V(e_p / z) - z \right) f(q^{0}_{p} - q^{1}_{p}). \]
It follows that the Hessian matrix of $\pi^{\infty}_p(q^0_p,q^1_p)$ is:

$$D_2 = \begin{vmatrix}
\frac{\partial^2 \pi^{\infty}_p(q^0_p,q^1_p)}{\partial q^0_p \partial q^1_p} & \frac{\partial^2 \pi^{\infty}_p(q^0_p,q^1_p)}{\partial q^0_p \partial q^1_p} \\
\frac{\partial^2 \pi^{\infty}_p(q^0_p,q^1_p)}{\partial q^1_p \partial q^0_p} & \frac{\partial^2 \pi^{\infty}_p(q^0_p,q^1_p)}{\partial q^1_p \partial q^0_p}
\end{vmatrix}$$

$$= \begin{bmatrix}(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p \left( e_p V(e_p/z)-\alpha p \right) f \left( q^0_p-q^1_p \right) f \left( q^0_p \right) \end{bmatrix}$$

Therefore, if $(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p > 0$ and $e_p V(e_p/z)-\alpha p > 0$, that is $\bar{p}_s-\alpha \bar{p}_s > e_p V(e_p/z) > \alpha p$, then $(\partial^2 \pi^{\infty}_p(q^0_p,q^1_p))/(\partial q^0_p \partial q^1_p) < 0$ and $D_2 > 0$. So, under this context, the $\pi^{\infty}_p(q^0_p,q^1_p)$ is jointly concave in $q^0_p$ and $q^1_p$, and a unique order policy which maximizes $\pi^{\infty}_p(q^0_p,q^1_p)$ exists.

From $\partial \pi^{\infty}_p(q^0_p,q^1_p)/\partial q^0_p = 0$ and $\partial \pi^{\infty}_p(q^0_p,q^1_p)/\partial q^1_p = 0$, we have:

$$\begin{cases}
q^{0*}_p = F^{-1} \left( \frac{(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p}{(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p} \right) \\
q^{1*}_p = F^{-1} \left( \frac{\alpha q^1_p}{e_p V(e_p/z)+\alpha p} \right)
\end{cases}$$

and can get Lemma 2.

Proof of $P1$. From Lemma 2, taking the first derivatives w.r.t $w$, $o$ and $e_p$, respectively, we obtain:

$$\frac{dq^{0*}_p}{dw} = -\frac{1}{(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p} \cdot \frac{1}{f \left( F^{-1}(C) \right)} < 0, \quad \frac{dq^{0*}_p}{do} = -\frac{1}{(1-\alpha)\bar{p}_s-e_p V(e_p/z)+\alpha p} \cdot \frac{1}{f \left( F^{-1}(C) \right)} < 0, \quad \frac{dq^{1*}_p}{de_p} = \left( \bar{p}_s-\alpha \bar{p}_s \right) \left[ V(e_p/z)+e_p V(e_p/z)-\alpha p V(e_p/z) \right] \cdot \frac{1}{\left( 1-\alpha \bar{p}_s-e_p V(e_p/z)+\alpha p \right)^2} \cdot \frac{1}{f \left( F^{-1}(C) \right)} > 0.$$

In the same way, we can get $\frac{dq^{1*}_p}{dw} < 0, \frac{dq^{1*}_p}{do} < 0$ and $\frac{dq^{1*}_p}{de_p} > 0$. So $q^{0*}_p$ and $q^{1*}_p$ are decreasing in $(w, o)$ and increasing in $e_p$.

Proof of Lemma 3. Equation (9) can be further rewritten as:

$$\pi^z_p(Q_p) = \left( w-2\bar{p}_s \right) q^{0*}_p + \alpha q^{1*}_p + (1-\alpha)\bar{p}_s \int_{0}^{\frac{q^0_p}{q^0_p}} \left( t Q_p - q^{0*}_p \right) \varphi(t) dt$$

$$- e_p V(e_p/z) - \alpha p \int_{q^{0*}_p-q^{1*}_p}^{q^{0*}_p} F(x) dx - \left( c-2\bar{p}_s \mu \right) Q_p.$$

It follows that:

$$\frac{d\pi^z_p(Q_p)}{dQ_p} = - \left( c-2\bar{p}_s \mu \right) + (1-\alpha) \int_{0}^{\frac{q^0_p}{q^0_p}} t \varphi(t) dt$$
It follows from formulas above that $\pi_p(Q_p)$ is strictly concave in $Q_p$, and a unique components production quantity $Q_p^n$ which maximizes $\pi_p(Q_p)$ exists. By the first-order optimality condition, we can get Lemma 3.

Proof of Lemma 4. Equation (12) can be further rewritten as:

$$
\pi_p(\hat{Q}_p) = \left(w - \bar{p}_s\right) q_p^0 + o q_p^1 + \left(w - \alpha \bar{p} - e_p V(e_p / z)\right).
$$

$$
\frac{d\pi_p(\hat{Q}_p)}{d\hat{Q}_p} = \left(w - \alpha \bar{p} - e_p V(e_p / z)\right) \int_0^{\hat{Q}_p} \left( f(x)dx - \int_0^{t \hat{Q}_p} f(x)dx \right) \varphi(t)dt
$$

$$
- \left(e_p V(e_p / z) - \alpha \bar{p}\right) \int_{q_p^0 - q_p^1}^{q_p^0} F(x)dx
$$

$$
+ (1 - z)\bar{p}_s \int_0^1 \left( \int_0^{t \hat{Q}_p} f(x)dx - \int_0^{t \hat{Q}_p} f(x)dx \right) \varphi(t)dt
$$

$$
- (c - \bar{p}_s \mu) \hat{Q}_p.
$$

It shows that:

$$
\frac{d^2\pi_p(\hat{Q}_p)}{d\hat{Q}_p^2} = \left(w - \alpha \bar{p} - e_p V(e_p / z)\right) \int_0^{\hat{Q}_p} \left( f(x)dx - \int_0^{t \hat{Q}_p} f(x)dx \right) t \varphi(t)dt
$$

$$
- (1 - z)\bar{p}_s \int_0^1 f(t \hat{Q}_p) t \varphi(t)dt - (c - \bar{p}_s \mu),
$$

$$
\frac{d^2\pi_p(\hat{Q}_p)}{d\hat{Q}_p^2} = \left[w - \alpha \bar{p} - e_p V(e_p / z)\right] \int_0^{\hat{Q}_p} f(t \hat{Q}_p) t^2 \varphi(t)dt
$$

$$
- (1 - z)\bar{p}_s \int_0^1 f(t \hat{Q}_p) t^2 \varphi(t)dt
$$

$$
< \left[\left(w - \bar{p}_s\right) - \left(e_p V(e_p / z) - \alpha \bar{p}\right)\right] \int_0^{\hat{Q}_p} f(t \hat{Q}_p) t^2 \varphi(t)dt < 0.
$$

So $\pi_p(\hat{Q}_p)$ is strictly concave in $\hat{Q}_p$. From $\frac{\partial^2\pi_p(\hat{Q}_p)}{\partial \hat{Q}_p^2} = 0$, we get Equation (13).
Proof of $P2$. To achieve the supply chain coordination, we have to ensure $Q_i^* = Q^*$. From Equations (13) and (2), we can get:

$$
(1-\alpha)\bar{p}_s \int_0^1 F(tQ^*) t\varphi(t) dt - (w - \alpha\bar{p} - e_p V(e_p/\alpha)) \int_0^1 \bar{p}_s F(tQ^*) t\varphi(t) dt = (\bar{p}_s \mu - c).
$$

Then simplify the equation by representing $\int_0^1 F(tQ^*) t\varphi(t) dt$ with $(c - \alpha\bar{p}_s \mu)/((1-\alpha)\bar{p}_s)$. It follows that $w = \alpha\bar{p} + e_p V(e_p/\alpha)$.

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Minimizing the risk of seaport operations efficiency reduction affected by vessel arrival delay

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Abstract
Purpose – In seaport industries, vessel arrival delay is inevitable because of numerous factors, e.g. weather, delay due to the previous stop, etc. The period of delay can be as short at 15 min or as long as a few days. This causes disruption to the planned sea operation operations, and more importantly, to the resources utilization. In traditional berth allocation and quay crane assignment problems (BA-QCA), the risk of vessel arrival delay has not been considered. Accordingly, the purpose of this paper is to employ a proactive planning approach by taking into consideration the vessel arrival delay into the optimization of BA-QCA problems.

Design/methodology/approach – In the existing BA-QCA problems, vessel arrival time is usually deterministic. In order to capture the uncertainties of arrival delay, this paper models the arrival time as a probability distribution function. Moreover, this paper proposes to model the delay risk by using the period between the expected arrival time and the expected waiting time of a vessel. Lastly, the authors propose a new modified genetic algorithm and a new quay crane assignment heuristic to maximize the schedule reliability of BA-QCA.

Findings – A number of numerical experiments are conducted. First of all, the optimization quality of the proposed algorithm is compared with the traditional genetic algorithm for verifying the correctness of the optimization approach. Then, the impact of vessel arrival delay is tested in different scenarios. The results demonstrate that the impact of vessel arrival delay can be minimized, especially in the situations of high vessel to potential berth ratio.

Research limitations/implications – The proposed vessel arrival modeling approach and the BA and QCA approach can increase the operations efficiency of seaports. These approaches can increase the resource utilization by reducing the effect of vessel arrival delay. In other words, this can improve the throughput of seaport terminals.

Originality/value – This paper proposes to minimize the delay risk based on the conditional probability of the vessel completion time based on the previous vessel at the assigned berth. This modeling approach is new in literature.

Keywords Risk management, Berth allocation, Delay risk, Quay crane assignment, Seaport operations

Paper type Research paper

1. Introduction
Seaport is regarded as the interface between sea and inland transportations, mainly dealing with the handling of import and export container operations, including loading and unloading, and storages (Mutty et al., 2005). Operations in a seaport are triggered by the arrival of vessels. However, the planning of operations and resources allocation usually starts a few weeks earlier than the actual arrival. When a vessel arrives at the seaport, it will be assigned to a berth and wait for the service of quay cranes to unload and load of containers (Steenken et al., 2004). Import containers will be transported to storage temporarily at the yard by internal tractors, and wait for customers to pick-up. For export containers, after the containers are brought in by external tractors, they will be stacked and stored at the yard until the vessel for shipping them comes (Ng and Mak, 2006).
Containers will be transported to the quay side and get loaded onto the vessel by quay cranes as outlined in Figure 1.

Berth allocation plays an important role in determining the terminal productivity as the handling time for a specific vessel is not necessarily the same at every berth (Bierwirth and Meisel, 2010). Concurrently, utilization of costly terminal infrastructure determined by berth allocation planning plays an important role in enhancing terminal profitability (Zhen, 2014). A good berth allocation scheme can help to minimize the total service time of all ships and thus enable the port to serve more ships (indeed it is the number of containers being handled) for higher terminal profits. Besides other than the assignment of quay space to vessels, assignment of service time (or service order) to vessels is another indispensable component of berth allocation. As there is no longer berth leased by specific ship lines or vessel companies in majority of ports, vessels of various sizes and various cargo handling volume at a particular port of call competing for the same berth for handling. As a result, there are always concerns from both terminal operator and vessel companies regarding the service order and the service priority.

The actual arrival time of vessel is often deviated from the scheduled ones (Xu et al., 2012). According to a survey conducted by Drewry Shipping Consultants, more than 40 percent of the vessels on global liner services have been delayed for 1 or more days (Drewry, 2006). This induces severe operations problems to seaport terminals, for example, damaging the scheduled operations reliability of berth allocation, quay crane assignment, and yard storage plans, and affecting the scheduling of internal tractors (Hasheminia and Jiang, 2017). To tackle this problem, this paper is divided into the following sections. Section 2 presents a literature review. Section 3 discusses the problem background and formulation. Section 4 presents the proposed optimization algorithm. Section 5 conducts the numerical experiments and result discussion. Lastly, the paper will conclude with Section 6.
2. Literature review

With the rapid growth of globalization and international trading, seaports play an important and major role in global supply chain (Kim and Moon, 2003). With the challenge of global and local competition, pressure is placed on seaport for faster turnaround of calling vessels and better utilization of infrastructure (Nishimura et al., 2005; Stahlbock and Voß, 2008). Accordingly, optimization scheduling becomes critical. In seaport operations, berth allocation problems refer to the assignment of quay space and service time to the incoming vessels in order for them to conduct unloading and loading container operations (Bierwirth and Meisel, 2010).

In general, berth allocation needs to take into consideration the arrival time of vessels, physical constraints, e.g. vessel’s length and berth’s length, and other technical constraints, e.g. availability of cranes (Guan and Cheung, 2004). It is regarded as one of the key important factors that affecting the productivity of seaport as the handling time for a specific vessel may depends on the berth that it is to be handled (Imai et al., 2005; Cordeau et al., 2005). A good berth allocation plan can be measured in terms of cost saving, total waiting time, total handling time or even total service time. At the very beginning of the studies, Lim (1998) studied a model to maximize the amount of quay space used at any time with the assumption that once a ship is berthed. Later on, Li et al. considered “multiple-job-on-one-processor” pattern, where several jobs (vessels) can be processed by a single processor (berth) simultaneously. Numerical experiments for the first-fit-decreasing heuristic rule they proposed were conducted. Park and Kim (2003) study the berth allocation problems with an objective to minimize the costs of delayed departures of ships. Guan et al. considered a berth allocation problem with the objective of minimizing the total weighted flow time, which is the sum of waiting time and handling time of a vessel while the weights reflect the relative importance of vessels based on the delay cost of vessels. Their research was motivated by more efficient management of container traffic flow of container terminals in Hong Kong. They assumed vessel arrivals can be grouped into batches. Tree search procedure and a composite heuristic combining the pair-wise exchange heuristic and tree search procedure were considered and proposed. The computational experiments showed that the proposed composite heuristic is effective.

Unlike Li et al. who investigated the problems with fixed vessel’s handling time, Imai et al. (2005) and Chang et al. (2010) studied the problems with handling time being berth location-dependent. Imai et al. (2005) aim at minimizing the sum of service time for all vessels with the assumption that a vessel’s handling time depends on the quay location where a particular vessel is handled. Later on, Chang et al. (2010) further extend Imai et al. (2005) model by incorporating the relationship between vessel draft and water depth alongside in the berth allocation planning. This is known as crane assignment problems later on. The idea of quay crane assignment is to answer the questions of which individual crane(s) is/are to be assigned to particular vessel for loading/unloading and how many quay cranes should be assigned to serve a particular vessel. Tremendous work have been done afterwards (Tavakkoli-Moghaddam et al., 2009; Meisel and Bierwirth, 2006, 2009). The crane assignment is co-related with and highly affecting the berthing allocation decision as cranes are usually operating locally and impossible to be exchanged between different berths (Günther and Kim, 2006). However, most of the work assumes deterministic vessel arrival time. Accordingly, the reliability of the schedule may suffer.

Regarding the impacts of vessel arrival delay, an extensive literature has been done to mitigate the risk of delays. For example, some studies focus on developing real-time schedule recovery policies subject to various uncertainties and disruptions caused by vessel arrival delays (Li et al., 2016). Some studies suggested implementing different pricing strategies, known as congestion pricing, for gateway charges and the relationship between the charges and the capacity investment (Yuen et al., 2008; Jiang et al., 2017). Some studies
focus on recovery strategies, for example Loh and Thai (2016) study a Port-Related Supply Chain Disruption management model that involves the application of business continuity management, risk management, and quality management theories in order to increase port resilience ability. Justice et al. (2016) study how resilience processes are undertaken by US seaports to tackle disruptions. The last stream of literature focus on the reliability of vessels schedules by improving seaport operations. In this stream, studies focus on how to optimize the seaport facility allocation scheduling, i.e. berth allocation, and quay crane assignment, in order to mitigate the risks (Imai et al., 2008; Lee et al., 2008).

3. Problem description and formulation

We studied a seaport with $N$ number of quay side ($n \in N$) and each quay side $n$ with $B$ number of berths ($b_n \in B_n$) with a maximum $Q_n$ number of quay crane available ($q_n \in Q_n$). Given a set of incoming vessels ($v \in V$) with arrival time ($\alpha_v$), which follows its own normal distribution $f(x) = N(\mu, \sigma)$, and expected departure time ($d_v$). Each vessel consists of a number of containers to be handled ($\beta_v$). Our aim is to maximize the departure reliability of the vessels as in the following equation:

$$\text{Max } z = \sum_v p_v v \in V, \quad (1)$$

where $p_v$ is the conditional probability of vessel $v$ to be completed before expected departure time based on the completion time of the previous vessel $v'$ at the same berth assigned. Since the probability of a vessel $v$ to be completed ($\bar{c}_v$) before its expected departure time can be found by:

$$P(v) = \int_{\bar{c}_v}^{d_v} f(x) dx, \quad (2)$$

where the expected completion time $\bar{c}_v$ of a vessel $v$ is equal to:

$$\bar{c}_v = s_v + \frac{\beta_v}{\sigma_v} \times 2, \quad (3)$$

where $\sigma_v$ is the variable defining the number of quay cranes being assigned to service the vessel $v$ at berth $b_n$, and $s_v$ is a variable defining the starting time of vessel $v$. $\alpha_v$ is equal to the total number of quay cranes available in the berth allocated until completion, i.e. $\alpha_v = y_{b_n,1} + y_{b_n,1} + 1 + \ldots$, where $y_{b_n,t}$ is the decision variable defining the number of quay crane assigned to the berth $b_n$. We denote another decision variable $x_{b_n,v} = 1$ if the vessel $v$ is assigned to berth $b_n$. In addition, the constant 2 is used to denote the average time required to handle 1 piece of container. Noted the constant can be amended as needed. In this paper, the value of 2 is being used due to common practice. Moreover, since $s_v \geq \alpha_v$, thus $\bar{c}_v$ also follows the normal distribution with $f(x) = N(\bar{c}_v, \sigma_v)$. Accordingly, the conditional probability of $p_v$ can be found in the following equation:

$$p_v = P(v|v'). \quad (4)$$

We considered vessels can be occupied only 1 berth and is no interchangeable as shown in the following equation:

$$\sum_b \sum_n x_{b_n,v} = 1, \forall v. \quad (5)$$
Moreover, the quay crane is not interchangeable between different quay side, but
interchangeable between berths along the same quay side as shown in the following equation:

\[ \sum_n y_{h,t} \leq Q_n, \forall t, \forall b. \]  

4. Proposed modified genetic algorithm with competition QC assignment
heuristics
To tackle the problem, we propose a new algorithm named a Modified Genetic Algorithm
with Competition QC Assignment heuristics (GA-CQCA), which consists of two main parts –
a modified genetic algorithm and a quay crane assignment heuristics. The main purpose of
the modified genetic algorithm is to determine the berth allocation problem and the
 corresponding service sequences for vessels. The CQCA is to determine the QC assignment
based on the urgency of the vessel. In both levels, roulette wheel selection will be applied for
the generation of the mating pool. Moreover, during each evolution, elitist strategy will be
applied to avoid the lost of the best chromosome(s). The details are as follows.

4.1 Encoding and decoding of chromosome
The chromosome is encoded in a two dimensional matrix with length equal to the total
number of incoming vessels \(|V|\), and width equal to three as shown in Figure 2. The first row
represents the vessel number. The second row in the chromosome represents the quay
number and the third row represents the berth number. Assuming we are considering a
seaport with two quay sides. One of the quay sides, denoted as Quay 1, has 2 berths; while
another quay side, denoted as Quay 2, has three berths. As shown in the sample, the
chromosome can be decoded as shown in Figure 2. The corresponding berth allocation and
the service sequence can be interrupted as shown in Figure 3, which shows that v1 and v6
are assigned to Berth 1 in Quay side 1 with the service sequence of v1 followed by v6.

4.2 Evolution operation – crossover
In order to avoid random search, we avoid applying traditional single point or uniform
crossover approaches, which may induce too much changes to the chromosome structure
in this problem. Accordingly, we propose to apply crossover point based on the number
of berth in a quay side. In this connection, a quay side will be randomly selected and a
berth will be randomly selected for crossover. For example in Figure 4, assuming Berth 2
of Quay 1 is randomly selected. Then the vessels in Berth 2 of Quay 1 will be imported into
the other chromosome as the shading genes in Figure 4. Since the service sequence of

\begin{verbatim}
Figure 2.
Sample encoding of chromosome
\end{verbatim}

\begin{verbatim}
Vessel | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10
Quay  | 1 | 1 | 2 | 1 | 2 | 1 | 2 | 2 | 1 | 1
Berth | 1 | 2 | 1 | 2 | 3 | 1 | 2 | 1 | 2 | 2
\end{verbatim}

\begin{verbatim}
Figure 3.
Sample decoding of chromosome
\end{verbatim}

\begin{verbatim}
Quay 1  Berth 1 | v1   v6
          Berth 2 | v2   v4  v9  v10
Quay 2  Berth 1 | v3   v8
          Berth 2 | v7
          Berth 3 | v5
\end{verbatim}
vessel is defined from the left to the right, for those newly imported vessels, they will be put to the very right so that they will not affect the original sequence. Then the service sequence will be optimized by using exhaustive search approach, which is applicable in this case due to the small problem scale here.

4.3 Evolution operation – mutation
Similar as crossover, to avoid random search, we propose to apply 0.1 mutation rate. A vessel will be randomly selected to undergo mutation, which will be mutated into another quay side or berth number. For example as shown in Figure 5, assuming v3 is randomly being selected, it will be randomly mutated to any other berth of any quay. Similarly, after the changes, the mutated gene will be to the very right and exhaustive search will be conducted to optimize the service sequence.

4.4 Quay crane assignment – CQCA heuristics
Since our objective is to maximize the schedule reliability, we propose a CQCA heuristics which is based on the urgency and vessel arrival delay variance for assignment. In each time step \( t \), we determine a slack time \( s_{it} \) for all the vessels \( i \) in the same quay side. It is determined by assuming all the available quay cranes in the quay side are allocated to that vessel. The idea of \( s_{it} \) is to indicate the remaining time after the expected completion of vessel \( v \). In other words, it represents the urgency of the vessel. Thus, the percentage of quay crane being distributed among the berths along the same quay side \( b_{nt} \) \( (y_{b_{nt}}) \) is determined by the following equation:

\[
y_{b_{nt}} = \left(1 - \frac{s_{it}}{\sum s_{it}}\right), \forall t \forall n,
\]

\( (7) \)
and the number of quay crane \( y_{b_n}^N \) is then equal to the following equation:

\[
y_{b_n}^N = \left[ \frac{Q_n \times y_{b_n}^{Sb}}{y_{b_{nt}}^{Sj}} \right] \forall t, \forall n
\]  

(8)

Then, the number of quay crane will be assigned to individual berth according to the one most in needs (i.e. the one with smallest \( s_{ij} \)) to the least. Moreover, the remaining quay crane \( (Q_n - \sum_{b_n} y_{b_n}^N) \) will be assigned to the berth with the same assignment logic. The advantage of this approach is to let the QC assignment dynamically changing according to the urgency of the vessel along the time steps.

5. Numerical experiments
The objective of the numerical experiments is with two purposes: to test the optimization performance of the proposed GA-CQCA over the traditional GA approach; and to test the significance of considering vessel delay variance over the traditional deterministic one. We conducted our experiment on a computer with i7 CPU and 32G ram. We randomly generated different scenarios as shown in Table I. We simulate different terminal scales and with different shipping uncertainties. The number of quay is ranged from 2 – 8 as in 2nd column of Table I, and each quay will randomly generate a number of berths ranging as in the 3rd column. The number of incoming vessel is list in the 4th column. Lastly, the

<table>
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<th>Vessel</th>
<th>Variance</th>
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Table I.  
Problem parameters of testing instances
deviation of shipping uncertainties in list in the last column. Moreover, we set the number of containers will be generated between (8,000 to 20,000), and the time step \( t \) is set equal to 30 min, which is the commonly existing practice in many seaport terminals.

5.1 Testing the performance proposed methodology GA-CQCA

First of all, we test the performance of the proposed GA-CQCA over the traditional GA by comparing the solution quality and the computational time required. In order to compare only the solution quality, vessel arrival time will be set as deterministic, in other words, variance will be set to 0 here. We applied uniform crossover with crossover rate 0.1 and mutation rate 0.1 to avoid random search for the traditional GA. We set the maximum computational time to be 120 min. For each instance, 50 individual runs will be conducted to obtain the average, minimum, and maximum solutions for comparison as shown in Table II.

To get a better understanding of the solution, we convert the optimal value \( z \) into a reliability percentage as follows:

\[
z = \left(\frac{z}{|V| \times 50}\right) \times 100
\]

The results indicate that the performance of the proposed GA-CQCA performs better than the traditional GA in terms of better solution quality obtained. Overall speaking, it is found

<table>
<thead>
<tr>
<th>Scale</th>
<th>Traditional GA</th>
<th>GA-CQCA</th>
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Table II.
Summary of the solutions obtained for numerical experiment 1
that the average schedule reliability obtained by the proposed GA-CQCA is higher than the ones obtained by the traditional GA in all the instances. Moreover, it is found that when the problem scale is getting larger, the deviations of the solution obtained by the traditional GA are getting larger, e.g. Instance 9 in large scale, the deviation is from minimum 70.5 to the maximum of 81.1 with an average of 75.6. It implies the stability of the performance of the traditional GA is getting worse due to the large problem scale. For the same instance, the performance of the proposed GA-CQCA becomes more stable with a minimum value of 9.3 and a maximum of 98.7 with an average of 97.4. The deviation is obviously much smaller.

Regarding the computational time, the proposed GA-CQCA also outperforms the traditional GA. The times required by the proposed GA-CQCA even for the small scale problems are already much shorter than that of the tradition GA, e.g. < 1 min for instance 4 in small scale problem. The time required for large scale problem, e.g. instance 9 required by the traditional GA was stopped at 120 min due to the maximum time allowed. However, the proposed GA-CQCA requires only 10 min.

5.2 Testing significance of considering vessel delay variance

The objective here is to test the significance of considering vessel arrival delay variance. Accordingly, we randomly generate arrival delay variance for each instance in Table I with small (0.2~0.5), medium (0.8~1.2), and large (1~3). Similarly, each instance has run individually for 50 times. In both with and without the consideration of vessel arrival delay variances, the algorithm GA-CQCA will be applied. Therefore, the computational time becomes not very meaningful and therefore ignored. The results are summarized in Table III.

Overall speaking, one can found that the average reliability of the schedules in the case of without the consideration of variance is ranging from the lowest 8 in the instance 1 of large scale problem to the most reliable one in instance 2 and instance 5 of small scale with a reliability value of 26. These values are generally much lower than those obtained by those obtained by considering variance. Moreover, one can see that there is no strong or obvious relationship between the reliability with the problem scale. This phenomenon can be explained by the objective of the optimization. In the cases of without considering variance, the algorithm will simply search for a solution that satisfying the due date requirement, which in fact is only the mean expected arrival time when the arrival is following a normal distribution. Thus, the reliability of the schedule tends to be small.

On the other hands, in the case of considering variance, the overall reliability is much higher with about 8x to 9x. Moreover, one can see that when the variances are getting larger, the reliability becomes lower. This may be due to the problem complexity. Furthermore, one can see that when the number of vessels is less but with more number of berths, the reliability generally is better. This is because more choices are available for the algorithm to search for a better berthing position for the vessels.

6. Conclusions

Managing risk of vessel arrival delay is crucial to seaports industry because it severely jeopardizes the scheduling reliability. Vessel arrival delay commonly happens. In this connection, an extensive amount of research has been conducted to mitigate the risk. Although berth allocation and quay crane assignment has been studied for long, there is a lack of papers studying the impacts of vessel arrival delay on the berth allocation and quay crane assignment problems (BA-QCA) schedule determined. Traditionally, vessel arrival time is assumed to be deterministic. In this paper, we propose to model the vessel arrival time to follow its own normal distribution in order to make it to be more realistic. Moreover, we model the expected vessels completion time by using conditional probability based on the completion time of the previous vessel on
the same berth. To deal with the problem, we propose a new modified genetic algorithm with a competition based heuristic approach to determine the quay crane assignment along the time steps so as to make the algorithm dynamically adjusting the quay crane assignment according to the real situation. The proposed algorithm is tested by conducting a number of numerical experiments. The result indicates that the proposed algorithm performs better than the traditional one. Moreover, the importance of considering vessel arrival delay is also tested by comparing with the situation of without considering variance. The results indicate that schedule reliability in average in much lower if variance is not being considered. On the other hands, although the reliability of the schedule may still reducing in large scale problem due to the problem complexity, overall speaking the schedule reliability of considering variance is much better than that of without. Therefore, this finding concludes that vessel arrival delay variance is important and should be considered in BA-QCA.

Currently, this paper successfully demonstrated the importance of considering arrival uncertainties in seaport operations. Moreover, the proposed algorithm also demonstrated its robustness in minimizing the effect imposed by arrival uncertainties. In seaport operations, uncertainties may also existing in quay crane handling operations, which also affect the service completion time of a vessel. Therefore, it is suggested that more effort can be researched on involving handling uncertainties with arrival uncertainties.

<table>
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Table III. The optimization results obtained by with and without consideration of variance.
References


**Further reading**


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Managing bioethanol supply chain resiliency: a risk-sharing model to mitigate yield uncertainty risk

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College of Economics and Management, South China Agricultural University, Guangzhou, China

Abstract
Purpose – The purpose of this paper is to propose a risk-sharing model to coordinate the decision-making behavior of players in a cassava-based bioethanol supply chain under random yield and demand environment, so as to mitigate the yield and demand uncertainty risk and improve the bioethanol supply chain resiliency and performance.

Design/methodology/approach – The decision-making behavior under three models, namely, centralized model, decentralized model and risk-sharing model, are analyzed. An empirical test of the advantages and feasibility of the proposed risk-sharing model, as well as the test of yield uncertainty risk, risk-sharing coefficients and randomly fluctuating cassava market price on the decision-making behavior and performances are provided.

Findings – Though the proposed risk-sharing model cannot achieve the supply chain performance in the centralized model, it does help to encourage the farmers and the company to increase the supply of cassava and achieve the Pareto improvement of both players compared to the decentralized model. In particular, these improvements will be enlarged as the yield uncertainty risk is higher.

Practical implications – The findings will help decision makers in the bioethanol supply chain to understand how to mitigate the yield uncertainty risk and improve the supply chain resiliency under yield and demand uncertainty environment. It will also be conducive to ensure the supply of feedstock and the development of the bioethanol industry.

Originality/value – The proposed risk-sharing model incorporates the yield uncertainty risk, the random market demand and the hierarchical decision-making behavior structure of the bioethanol supply chain in the model.

Keywords Cassava, Bioethanol supply chain, Risk-sharing, Yield uncertainty

1. Introduction
As a promising alternative to fossil fuels and a solution to reduce the greenhouse gas (GHG) emissions, bioethanol is playing an increasingly important role in global society in the past decades (Li and Hu, 2014; Ba et al., 2016; Meyer et al., 2016). This issue is especially important in China, the largest primary energy consumer and emitter of GHG in the world (Ye et al., 2018). In recent years, China has launched programs to promote the production of bioethanol to meet the ever-increasing energy consumption and to achieve the GHG emissions reduction target. Figure 1 shows that China’s production of bioethanol is increasing rapidly in previous years. However, bioethanol is still a source of renewable energy that is generally underutilized in China. The production of bioethanol in 2015 is only 2.3m tonnes, which is still significantly lower than the 10m tonnes target in 2020 (Ye et al., 2017).

The study is supported by National Natural Science Foundation of China (71771090; 71471066; 71371006; 71420107024).
To promote the development of bioethanol industry, the sufficient supply of feedstock is extremely important. But China’s bioethanol industry is suffering from an undersupply of agricultural feedstock for bioethanol production (Ye et al., 2018). Meanwhile, China used to rely heavily on consumable grain crops, such as corn and wheat, to produce bioethanol. However, after the 2007–2008 global food crisis claiming to be related to bioethanol production and the accompanying food vs fuel debate (Timilsina and Shrestha, 2011), the Chinese Government abolished the government subsidy on corn-based bioethanol industry in 2016 (Jin, 2014). Alternatively, the production of bioethanol from non-edible feedstock becomes the Chinese Government key support project, within which cassava is the most important and attractive one due to its high-starch content and good environment adaptability (Leng et al., 2008; Jakrawatana et al., 2016). Despite the increasing production of cassava every year, the demand for cassava in China, however, still far exceeds the supply and, consequently, relies heavily on the import from other countries, as shown in Figure 2.

Therefore, how to encourage the production of cassava to ensure sufficient feedstock for bioethanol industry in China. A couple of risks deeply influence this issue. On the one hand, the undersupply of feedstock is due to the scattered and low intensive cultivation by small-scale farmers with little use of mechanized planting (Liu et al., 2013), as well as the uncertainties related to weather variability, which directly caused yield uncertainty and the mismatch between farmers’ supply and company’s demand. On the other hand, considering the short shelf life of bioethanol, strict storage and transportation environment and stochastic market demand (Meyer et al., 2016), the bioethanol supply chain is riskier than traditional supply chain. Moreover, the target to maximize their own expected profit by farmers and
companies, which lead to double marginalization effect, will undermine the sufficient supply of cassava. Building the connection between farmers and companies to coordinate their decision-making behaviors and establish a community of interests is a feasible way to handle these problems, and a risk-sharing model is introduced to this specific supply chain. Meuwissen et al. (2001) studied risk-sharing management strategies and concluded that risk-sharing strategies do help farmers manage agriculture risks from a theoretical and empirical perspective. He and Zhang (2010) indicated that proper cost parameters setting in risk-sharing model will have a positive impact on supply chain performance and reduce the double marginalization effect. Given that knowledge, the bioethanol production company and the cassava planting farmers have adopted contract farming scheme[1] and formed a supply chain to increase farmers’ productivity, facilitate the adoption of new production technologies and farmers’ access to higher-end markets, and boost total profits for both players (Niu et al., 2016; Ye et al., 2017).

Despite the advantage of contracting farming scheme in enhancing the supply of cassava and helping farmers gain market access, two unique characteristics due to the nature of agricultural products and the players in the contract farming supply chain, however, still affect the supply of cassava for bioethanol production. First, the natural disasters (e.g. earthquakes, drought, hurricanes and floods) will post heavily impact on the yield of cassava (Kazaz and Webster, 2011), and thereby increase the uncertainties and supply disruption risks, a distinct key element in supply chains (Tse et al., 2016). The natural disasters will also affect the profitability and performance of the players in the supply chain. Second, though the contract farming supply chain seeks to improve the competitive performance of the entire network through integration and cooperation among players beyond the boundaries of a single enterprise (Lockamy, 2014), the bioethanol production company and the cassava production farmers, however, are still separate entities in nature. Their decision-making behavior structure is complex and hierarchical, not from an integrated approach (Meyer et al., 2016; Ye et al., 2017), and inevitably, they would pursue the maximization of their own profits and harm the performance of the whole supply chain.

To tackle these two challenges in the bioethanol supply chain, the purpose of this paper is to design a risk-sharing model to coordinate the decision-making behavior in the cassava-based bioethanol supply chain by incorporating the uncertainty yield risk caused by the natural conditions and the competitive and interrelated decision-making behavior within the supply chain players, so as to help the decision makers in the bioethanol supply chain to understand how to mitigate the yield uncertainty risk and improve the supply chain resiliency under yield and demand uncertainty environment. It will also be conducive to ensure the supply of feedstock and the development of bioethanol industry.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the basic models and assumptions. The decision-making behavior under three models, namely, centralized model, decentralized model and risk-sharing model, is also analyzed in Section 3. An empirical test for the advantage and feasible of the proposed risk-sharing model, as well as the test of the yield uncertainty risk, the risk-sharing coefficients, and the random cassava market price on the decision-making behavior and performances are provided in Section 4. Finally, a summary of the research is given in Section 5. All technical proofs are provided in the Appendix.

2. Literature review
2.1 Supply chain resilience
With the development of global economy and changeable business environment, the supply chain risks deriving from both external environment (e.g. natural disasters and policies) and internal environment (e.g. economic cycle and supply chain partnership) will deeply influence the operational and financial performance of supply chain (Hendricks and Singhal, 2003).
Thus, supply chain resilience gains a major focus in supply chain risk management and becomes one of the critical domains of supply chain management (Pereira et al., 2014). However, the research on supply chain resilience is relatively in an embryonic stage and the definition is inconformity (Ponis and Koronis, 2012; Soni et al., 2014). Christopher and Peck (2004) proposed that the supply chain resilience can be defined as the ability of a system to recover from some disruptions with negative effects and unpredictable risk events to the initial stage or to move to a better state. Sheffi and Rice (2005) studied the resilient enterprise from a supply chain view and showed that a company’s resilience is related to its competitive position and the reaction of its supply chain. Datta et al. (2007) studied an agent-based computational framework under demand uncertainty to improve the operational resilience. Ponomarov and Holcomb (2009) indicated that the key elements of supply chain resilience and the interactions among them are still hard to identify. In spite of this, Carvalho et al. (2012) thought that the increasing number and frequency of supply chain uncertainties which can decrease the performance of the supply chain are serious than ever before. Vulnerabilities and negative disturbances must be overcome by a supply chain system. Wieland and Wallenburg (2013) explored the resilience domain from the perspective of customer value and further indicated that communicative and cooperative relationships have a positive effect on resilience. Mandal (2017) investigated the influence of supply and demand competence on supply chain resilience and its impact on a firm’s operational and relational performance. Different from the research above which focuses on the theoretical conclusions of the phenomenon, this study aims to mitigate the supply chain resilience under stochastic yield and demand by risk-sharing model and using empirical test of Chinese cassava-based bioethanol supply chain to illustrate the advantages and feasibility of the proposed model.

2.2 Supply chain dual uncertainties

2.3 Bioenergy supply chain
The worldwide growing demand for bioenergy has attracted the attention of scholars. Plenty of studies have researched the bioenergy supply chain, but many of them aimed to analyze the energy efficiency and policy advice of bioenergy. For example, Liu et al. (2013) evaluated the energy and GHG performance of cassava-based fuel ethanol under different agricultural planting modes. Holmgren et al. (2015) and Jonker et al. (2016) analyzed the impact on the GHG emissions of the raw material supply chain. Jakrawatana et al. (2016) identified the cost and energy loss by using material flow cost accounting, and investigated the relationship between technology development and productivity promoted of ethanol in Thailand. In recent years,
an increasing number of research papers report on the supply chain coordination research in the field of bioenergy systems. Nasiri and Zaccour (2009) proposed a three-stage supply chain to analyze the process of utilizing biomass for power generation based on the Nash equilibrium. Sharma et al. (2013) showed that the coordination of the biomass supply chain will largely affect its performance. Sun et al. (2013) studied the optimal strategies for managing competitive agri-biomass supply chain and evaluated the industrial coexistence conditions. Wen and Zhang (2015) structured a mixed acquisition mode to coordinate China’s straw supply chain, which can be applied in practice and lead to lower cost for power plants. Ye et al. (2018) studied a biofuel supply chain coordination problem by proposing three types contracts (overproduction risk-sharing contract, underproduction risk-sharing contract and mixed contract) under random yield. Ye et al. (2017) proposed a production cost-sharing contract to coordinate the bioethanol supply chain under CVaR criterion. Liang et al. (2017) proposed a revenue-sharing model to discuss the supply chain performance between wind farms and wind turbine manufacturers in the aftermarket of wind turbine.

However, the risk-sharing model we proposed in this paper is distinguished from these studies. First, we assume both the yield of cassava and the demand for bioethanol are random, which will thereby increase the mismatch risk between the supply and demand of cassava and bioethanol in the supply chain. To mitigate the uncertainties and supply disruption risks, we propose the risk-sharing model to increase the input quantity of cassava and assume the bioethanol supply chain will replenish the insufficient supply of cassava from the spot market. Moreover, we discussed the impact of random fluctuated cassava spot market price and the yield uncertainty risk on the effectiveness of the proposed risk-sharing model. Second, the proposed risk-sharing model takes the hierarchical decision-making behavior structure of the bioethanol supply chain and the players’ rationalities into consideration, aiming to seek reasonable risk-sharing coefficients to achieve the Pareto improvement of both players, instead of the integrated and perfect one. Moreover, we discussed the impact of low to high yield uncertainty risk on the proposed risk-sharing model, and the results manifest the improvement of the proposed risk-sharing model will be enlarged with the higher yield uncertainty risk.

3. Problem formulation

We consider a cassava-based bioethanol supply chain consisted of a bioethanol company that produces cassava-based bioethanol and n small-scale farmers that supply cassava following the contract farming scheme. Using a pre-harvest agreement, the bioethanol company and farmers decide the conditions governing the sale of the cassava, such as time and location of sales, quality and price.

The bioethanol company signs a purchasing contract with the farmers and promised to purchase q(tonnes) cassava at a purchasing price of $\omega$(RMB/tonne) from the farmers. Then the farmers determine the input quantity of cassava $Q$(hm$^2$) they will plant with the unit planting cost of $C$(RMB/hm$^2$). To ease the computational burden, we assume the n small-scale farmers are homogenous in terms of planting cost and input quantity decisions. Due to the impact of natural conditions such as weather, pests and diseases, the yield of cassava is random (Kazaz and Webster, 2011). Therefore, for each farmer’s input quantity $Q$, the realized yielded cassava is $Qu$ (tonnes), where $u$ is random with a continuous probability density function $f(u)$, a cumulative distribution function $F(u)$ and $E(u) = \mu$(tonnes/hm$^2$).

In the harvest season, the bioethanol company purchases the realized yielded cassava from the farmers and processes the cassava into bioethanol with unit processing cost $y$ (RMB/tonne) and conversion ratio $v$(tonnes/tonne), then sell the bioethanol to the market at a retail price $P$(RMB/tonne). The market demand of the bioethanol $x$ is random with a continuous probability density function $g(x)$, a cumulative distribution function $G(x)$ and $E(x) = \bar{x}$(tonnes). Due to the random yield of the cassava and random demand for the
bioethanol, there might be a mismatch between the supply and demand of the cassava and bioethanol in the supply chain. The supply chain will purchase the insufficient supply of cassava from the spot market at price $C_e$(RMB/tonne) while sell the excess cassava to the spot market and get the unit salvage value $s_1$(RMB/tonne). Similarly, the supply chain will get a unit salvage value $s_2$(RMB/tonne) for the excess bioethanol and face sales loss for the insufficient supply of bioethanol. In addition, we assume both the players in the bioethanol supply chain are risk-neutral and all information is common knowledge to them.

Throughout the paper, subscript $E$ ($F$) ($SC$) denotes a variable pertaining to the bioethanol company (farmer) (supply chain). Superscript $C$ ($D$) ($R$) denotes a variable pertaining to the centralized model (decentralized model) (risk-sharing model). Accordingly, $q^C$, $q^D$, $q^R$ and $\pi^C_E$, $\pi^D_E$, $\pi^R_E$ represent the bioethanol company’s order quantity decision and profit under centralized model, decentralized model and risk-sharing model, respectively. The variables related to the farmers and the supply chain are similar to those for the bioethanol company.

### 3.1 Centralized model

To set a benchmark, a centralized system decision model is considered. The company and farmers act as a community to maximize the whole supply chain profit in the centralized model. This community will decide a proper-order quantity $q^C$ and input quantity $Q^C$. Due to the random natural conditions, the realized yielded cassava might be less or more than the order quantity. If the yielded cassava $nQ^C \leq q^C$, the community will buy the insufficient cassava from the spot market at price $C_e$. If the yielded cassava is more than order quantity, the community will sell the excess cassava in the spot market and get the salvage value $s_1$ for each unit. Therefore, the supply chain’s profit is:

$$
E \left[ \pi^C_E \left( q^C, Q^C \right) \right] = P \cdot E_x \left[ \min \{ q^C v, x \} \right] + s_2 \cdot E_x \left[ \left( q^C v - x \right) \right]^+ + s_1 \cdot E \left[ \left( nQ^C \mu - q^C \right) \right]^+ - C_e \cdot E \left[ \left( q^C - nQ^C \mu \right) \right]^+ - nCQ^C - yq^C v. 
$$

(1)

**Theorem 1.** The optimal input quantity $Q^{C*}$ and order quantity $q^{C*}$ in the centralized model satisfy the following equations:

$$
Q^{C*} : \int_0^m \frac{q^C}{nQ^C} \mu f(\mu)d\mu = \frac{C - s_1 \pi}{C_e - s_1},
$$

(2)

$$
q^{C*} : P \int_0^m v g(x)dx + s_2 \int_0^m v g(x)dx - s_1 \int_0^m f(\mu)d\mu - C_e \int_0^m \frac{q^C}{nQ^C} f(\mu)d\mu = yv.
$$

(3)

All proofs are provided in the Appendix.

Let $m = q^C/nQ^C$. Assume a function $m: T(m) = \int_0^m \mu f(\mu)d\mu$. Knowing that $\partial T(m)/\partial m = mf(m) > 0$, $T(m)$ is a monotone function of $m$, thus there is a unique solution for Equation (2). Therefore, given other determined parameters, $q^C/nQ^C$ is a definite value, which means there is a one-to-one mapping between the order quantity $q^{C*}$ and the input quantity $Q^{C*}$.

### 3.2 Decentralized model

In this model, it is assumed that the company and the farmers act separately and there is no coordination and risk sharing between them. The interaction among the contract farming supply chain players is modeled using a leader–follower Stackelberg game. The company
acts as a leader to determine the optimal-order quantity of cassava purchased from the farmers to maximize the company’s profit, then the farmers act as followers to determine the optimal input quantity of cassava. In this analysis, the farmers’ optimal input quantity of the cassava to the company’s order quantity and wholesale price is solved first. Then the farmers’ response is embedded into the company’s decision-making behavior to decide the company’s optimal-order quantity.

Again, due to the random yield environment and the decision makers’ individual rationality, the realized yielded cassava might be less or more than the company’s order quantity. In the decentralized model, if \( nQ^D > q^D \), the company will only purchase the ordered quantity \( q^D \) according to the purchasing contract. Then the farmers will sell the excess cassava in the spot market and get the salvage value.

Under decentralized model setting, the farmer’s expected profit is:

\[
E[\pi^D_F] = \omega \cdot E_\mu \left[ \min \left\{ n\mu Q^D, q^D \right\} \right] + s_1 E_\mu \left[ \left( n\mu Q^D - q^D \right)^+ \right] - nCQ^D. \tag{4}
\]

**Theorem 2.** Under the decentralized model, the farmer’s profit is a concave function of the input quantity. The optimal \( Q^D_F \) satisfies the following equation:

\[
\int_0^{Q^D_F} \mu f(\mu) d\mu = \frac{C - s_1 P}{\omega - s_1}. \tag{5}
\]

The farmer’s optimal input quantity \( Q^D_F \) is linear to the company’s order quantity \( q^D \) under the decentralized model (similar to the proof of \( q^C/Q^C \)). Assume \( Q^D_F = M_1 q^D \), where \( M_1 \) is a constant determined by \( C, s_1, f(\cdot), \omega \) and \( n \).

Under decentralized model setting, the company’s expected profit is:

\[
E[\pi^D_E] = P \cdot E_x \left[ \min \left\{ x, q^D v \right\} \right] - C_e E_\mu \left[ \left( q^D - nQ^D F \right)^+ \right] - \omega \cdot E_\mu \left[ \min \left\{ nQ^D F, q^D \right\} \right] + s_2 \cdot E_x \left[ \left( q^D v - x \right)^+ \right] - yq^D v. \tag{6}
\]

**Theorem 3.** Under the decentralized model, the company’s profit is a concave function of \( q^D \). The optimal \( q^D_F^* \) satisfies the following equation:

\[
\int_{q^D F}^{\infty} g(x) dx = \frac{\omega - (\omega - C_e) \int_0^{1/nM_1} (1 - nM_1 f(\mu)) d\mu + yv - s_2 v}{(P - s_2) v}. \tag{7}
\]

### 3.3 Risk-sharing model

In the decentralized model, it can be seen that either the company takes the underproduction and potential sales loss risk when the farmers produce less fresh cassava than the expected order quantity \( (nQ^D \leq q^D) \) case), or the farmers take the overproduction and excess inventory risk when the farmers produce more cassava than the expected order quantity \( (nQ^D > q^D) \) case). Recall that China is suffering from an insufficient supply of cassava for bioethanol production, in this paper, it is proposed to design a risk-sharing model to
encourage the farmers to increase the input quantity of cassava, so as to ensure the sustainable supply of cassava for bioethanol production.

In the risk-sharing model, for the overproduction case (the farmers realized that yielded cassava is more than the company’s order quantity, that is, $nQ^R \pi > q^R$), the company will make a compensation price $t$(RMB/tonne) to the farmers for the excess cassava, so as to encourage the farmers to increase the input quantity of cassava. It should be noted that the company will not take away the overproduced cassava to avoid the holding cost, thus the farmers will get both the compensation and the salvage value of the excess cassava. Here we assume the sum of the salvage value and compensation for the excess cassava is less than farmers’ operation cost ($s_1 + t < C$) to avoid the farmers’ infinite input quantity situation. On the other hand, for the underproduction case (the farmers realized yielded cassava is less than the company’s order quantity, that is, $nQ^R \pi < q^R$), the farmers will be penalized for each unit of unfulfilled order at a penalty price $b$(RMB/tonne) since they have signed the purchasing contract with the bioethanol company. By doing this, the farmers can share the risk of potential sales loss with the bioethanol company.

Under the risk-sharing model, the farmer’s expected profit is:

$$E[p^F_R] = \omega \cdot E_\mu \left[ \min \left\{ nQ^R, q^R \right\} \right] - bE_\mu \left[ \left( q^R - nQ^R \mu \right)^+ \right]$$
$$+ (t+s_1)E_\mu \left[ \left( nQ^R \mu - q^R \right)^+ \right] - nCQ^R. \quad (8)$$

**Theorem 4.** Under the risk-sharing model, the farmer’s profit is a concave function of the input quantity. The optimal $Q^{R*}$ satisfies the following equation:

$$\int_0^{q^R/nQ^R} f(\mu) d\mu = \frac{C - (t+s_1)\pi}{\omega + b - (t + s_1)}. \quad (9)$$

Similar to the decentralized model, the farmer’s optimal input quantity $Q^{R*}$ is linear to the company’s order quantity $q^R$ under the risk-sharing model. Assume $Q^{R*} = M_2q^R$, where $M_2$ is a constant related to $C$, $t$, $b$, $f(\cdot)$, $\omega$ and $n$.

Under the risk-sharing model, the company’s expected profit is:

$$E[p^C_R] = P \cdot E_x \left[ \min \left\{ x, q^R v \right\} \right] + bE_\mu \left[ \left( q^R - nQ^R \mu \right)^+ \right] - tE_\mu \left[ \left( nQ^R \mu - q^R \right)^+ \right]$$
$$- C_3E_\mu \left[ \left( q^R - nQ^R \mu \right)^+ \right] - \omega \cdot E_\mu \left[ \min \left\{ nQ^R \mu, q^R \right\} \right] + s_2 \cdot E_x \left[ \left( q^R v - x \right)^+ \right] - yq^R v. \quad (10)$$

**Theorem 5.** Under the risk-sharing model, the company’s profit is a concave function of $q^R$. The optimal $q^{R*}$ satisfies the following equation:

$$\int_{q^{R*}_v}^{\infty} g(x) dx = \frac{\omega \cdot (\omega + b - t - Cx) \int_0^{1/nM_2} (1-n\mu M_2)f(\mu) d\mu - t(1-n\mu M_2) + yv - s_2v}{P - s_2v}. \quad (11)$$

4. **Empirical analysis**

From the above analysis, it can be seen that, though it can be proved that there exists the optimal-order quantity and input quantity of cassava, the closed-form solutions for them,
however, cannot be obtained due to the random demand and yield environment. Thus, it is very difficult to get the relationships among the parameters and the optimal decisions and profits intuitively. Therefore, in this section, we perform numerical examples to reveal how the demand and yield uncertainty impact the company and the farmers’ optimal decisions and profits in three models, so as to manifest the feasibility and advantage of the proposed risk-sharing model and provide managerial insights for practitioners.

We present an empirical application of the proposed models for cassava-based bioethanol supply chain in China. The key parameters are taken from the survey of cassava-based bioethanol industry in Guangxi province, which accounts for more than 60 percent of national cassava production in China (Ji et al., 2014). A cassava-based bioethanol supply chain consisting of a bioethanol company and 100 homogenous cassava farmers ($n = 100$) owns the following characteristics: $\omega = \text{RMB}550/\text{tonne}$, $C = \text{RMB}13,522/\text{hm}^2$, $s_1 = \text{RMB}200/\text{tonne}$, $C_v = \text{RMB}600/\text{tonne}$, $P = \text{RMB}6,000/\text{tonne}$, $v = \frac{1}{7}$, $y = \text{RMB}800/\text{tonne}$, $s_2 = \text{RMB}2,200/\text{tonne}$. Assume the random yield rate $\mu$ follows a uniform distribution with $\mu \sim U[A_1, B_1]$, where $A_1 = 31$ tonnes/ha. The random demand rate $x$ follows a uniform distribution with $x \sim U[A_2, B_2]$, where $x = 1,000$ tonnes. The coefficient of variation is defined as $CV = \text{standard deviation/mean value}$ to measure the uncertainty. $CV_U$ and $CV_D$ represent the uncertainty of yield and demand, respectively. Obviously, the higher the coefficient of variation is, the higher the uncertainty risk will be.

4.1 Effects of the risk-sharing coefficients and yield uncertainty on decisions and profits

In the risk-sharing model, it can be seen that the values of risk-sharing coefficients, penalty price $b$ and compensation price $t$, will have significant impacts on the company and the farmers’ optimal decisions and profits. Actually, the risk-sharing model can be reduced to two extreme cases. The first one is penalty case that only the farmers pay the penalty for the underproduction cassava, while the company does not pay the compensation for the overproduction cassava, i.e. $b \neq 0, t = 0$. The second one is the cost-sharing case that only the company pays the compensation to the farmers for the overproduction cassava, while the farmers do not pay the penalty for the underproduction cassava, i.e. $b = 0, t \neq 0$. However, in these two extreme cases, either the farmer or the company’s profit is less than that of decentralized model, thus the participation constraints of either of them cannot hold.

As a more powerful player in a contract farming supply chain (Ye et al., 2017), the company can set an ideal point of the risk-sharing coefficients to let the farmers’ profit under risk-sharing model just equal to that of decentralized model, so that the company can snatch all the improved profit of the supply chain in the risk-sharing model. However, to obtain a stable and reliable supply of cassava in the long term and to keep the stable and long-term relationship with the farmers, the company might give up part of the improved benefit by taking more risk-sharing responsibilities in the collaboration with the farmers in order to attract them to the cooperation program. Therefore, we suggest feasible ranges for the risk-sharing coefficients that can help achieve both the company and the farmers’ Pareto improvement through the risk-sharing model. Here, we set $(b, t) = (3, 28)$ as the feasible point of the risk-sharing coefficients combination to realize Pareto improvement for both the company and the farmers (the exact point of the risk-sharing coefficients combination can be bargained by the company and the farmers depending on their bargaining powers).

In addition, to show the effect of yield uncertainty on the company and the farmers’ optimal decisions and profits, let $CV_U$ range from 0.05 to 0.30 to cover low to high yield uncertainty ($CV_U \rightarrow 0.05$ represents low yield uncertainty, and $CV_U \rightarrow 0.30$ represents high yield uncertainty). Figure 3 shows the comparisons of the optimal decisions and profits among three models (centralized model, decentralized model and risk-sharing model with different risk-sharing coefficients combination) covering a low to high yield uncertainty environment. As can be seen in Figure 3, though the risk-sharing model cannot realize the supply chain
perfect coordination, it does help to encourage the farmers and the company to increase the input quantity and order quantity of cassava compared to a decentralized model. Though the profit of the whole supply chain can be improved through risk-sharing model despite the setting of risk-sharing coefficients combination, either the company or the farmers’ profit might be worse off due to unsuitable compensation and penalty prices setting compared to those of the decentralized model (see the $(b, t) = (3, 0)$ case for farmers’ worse off situation and $(b, t) = (0, 28)$ case for the company’s worse off situation in Figure 3). However, a proper setting of the risk-sharing coefficients combination can realize the Pareto improvement for both players (see the $(b, t) = (3, 28)$ case for Pareto improvement for both players situation in Figure 3).

Figure 4 shows the differences of the optimal decisions and profits between decentralized model and risk-sharing model covering a low to high uncertain yield environment in $(b, t) = (3, 28)$ case. From Figure 4, it can be seen that, the higher the yield uncertainty is,
the larger the differences between the order quantity and input quantity, as well as the company and the whole supply chain’s profits under decentralized model and risk-sharing model will be. Figure 4 also shows that the risk-sharing model is more conducive in terms of increasing the supply of cassava, the company’s profit and the supply chain’s profit compared to the decentralized model, and this improvement becomes more significant as the yield uncertainty risk gets higher. However, the improvement of the farmers’ profit under risk-sharing model becomes smaller as the yield uncertainty risk gets higher. This is because a higher yield uncertainty risk will lead to a lower realized yielded cassava, thus leading to a lower profit of the farmers.

4.2 Effect of the randomly fluctuating cassava market price

The market demand and market price of bioethanol is relatively stable due to Chinese government’s preferential policy. But due to the fact that the market price of cassava is affected by the actual yield of cassava in the season, the price will fluctuate from time to time. Therefore, in this section, it is assumed that the market price of cassava is random and follows normal distribution with $C_v \sim N(600,10)$, and see how the randomly fluctuating market price of cassava impacts the performance of the proposed risk-sharing model. Figure 5 shows the changes of optimal cassava input quantity and supply chain profit under three models with the randomly fluctuating market price of cassava in 100 cycles.

From Figure 5 it can be intuitively found that, with the randomly fluctuating cassava market price, the optimal input quantity and supply chain performance declined

![Figure 5](image-url)

**Figure 5.** The impact of randomly fluctuating cassava market price on the optimal cassava input quantity and supply chain profit under three models ($C_v = 0.1$)
significantly with the increase of yield uncertainty. And the vibration level increases rapidly under the same situation. This further illustrates the impact of yield uncertainty on the bioethanol supply chain. After taking a further look at Figures 4 and 5, it can be seen that the proposed risk-sharing model improves the anti-risk ability of the system, but it still has some problems. The company will order a larger quantity compared to the decentralized model to transfer the yield risk to the farmers. The company’s order quantity increases significantly in the risk-sharing model compared to what it is in the decentralized model. While the farmers’ input quantity increase from the decentralized model to the risk-sharing model is not as significantly as the company’s order quantity increase. Therefore, it can be concluded that the reduction percentage of the farmers’ expected profit will be higher than that of the company when the yield uncertainty increases. It is important to protect the farmers’ profit by letting the company share more of the high yield risk under this situation to improve the cassava supply and supply chain performance.

The average results of the 100 randomly fluctuating cassava market price cycles for the optimal cassava input quantity and supply chain profit under three models are then computed. As shown in Table I, define \( \Omega_{R-D} = ((Q^R_{SC} - Q^D_{SC})/(Q^D_{SC}))\% \) and \( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))\% \) as the improved percentage of the optimal cassava input quantity and supply chain profit in the risk-sharing model as compared to that of decentralized model, respectively. Similarly, define \( \Omega_{R-C} = ((Q^R_{SC} - Q^C_{SC})/(Q^C_{SC}))\% \) and \( \Delta_{R-C} = ((\pi^R_{SC} - \pi^C_{SC})/(\pi^C_{SC}))\% \) as the difference between the risk-sharing model and the centralized model regarding the optimal cassava input quantity and supply chain profit, respectively. Table I indicates that, with the randomly fluctuating cassava market price, the risk-sharing model outperforms the decentralized model in the cassava input quantity and supply chain profit (\( \Omega_{R-D} > 0 \) and \( \Delta_{R-D} > 0 \)). Moreover, with the higher yield uncertainty risk, the improvement on the performance of the risk-sharing model becomes larger (\( \Omega_{R-D} = 0.579\% \), \( \Delta_{R-D} = 0.051\% \) for \( CV_U = 0.05 \) case and \( \Omega_{R-D} = 2.344\% \), \( \Delta_{R-D} = 0.192\% \) for \( CV_U = 0.3 \) case in Table I). In addition, the supply chain performance of the risk-sharing model gets closer to that of the centralized model as the yield uncertainty risk gets higher (\( \Delta_{R-C} = -1.378\% \) for \( CV_U = 0.05 \) case and \( \Delta_{R-C} = -0.999\% \) for \( CV_U = 0.3 \) case in Table I). These results manifest the advantage and feasibility of the proposed risk-sharing model. The results show that the risk-sharing model can help increase the supply of cassava and supply chain profit under a yield and demand uncertainty environment.

<table>
<thead>
<tr>
<th>Model</th>
<th>Centralized model</th>
<th>Decentralized model</th>
<th>Risk-sharing model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CV_U = 0.05 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average ( Q ) (hm(^2))</td>
<td>2.254</td>
<td>2.072</td>
<td>2.084</td>
</tr>
<tr>
<td>Improved percentage</td>
<td>( \Omega_{R-D} = ((Q^R_{SC} - Q^D_{SC})/(Q^D_{SC}))% )</td>
<td>( \Omega_{R-C} = ((Q^R_{SC} - Q^C_{SC})/(Q^C_{SC}))% )</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
</tr>
<tr>
<td>Average ( \pi_{SC} ) (RMB)</td>
<td>1,925,532</td>
<td>1,898,028</td>
<td>1,898,999</td>
</tr>
<tr>
<td>Improved percentage</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
<td>( \Delta_{R-C} = ((\pi^R_{SC} - \pi^C_{SC})/(\pi^C_{SC}))% )</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
</tr>
<tr>
<td>( CV_U = 0.3 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average ( Q ) (hm(^2))</td>
<td>1.857</td>
<td>1.664</td>
<td>1.703</td>
</tr>
<tr>
<td>Improved percentage</td>
<td>( \Omega_{R-D} = ((Q^R_{SC} - Q^D_{SC})/(Q^D_{SC}))% )</td>
<td>( \Omega_{R-C} = ((Q^R_{SC} - Q^C_{SC})/(Q^C_{SC}))% )</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
</tr>
<tr>
<td>Average ( \pi_{SC} ) (RMB)</td>
<td>1,677,944</td>
<td>1,657,994</td>
<td>1,661,180</td>
</tr>
<tr>
<td>Improved percentage</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
<td>( \Delta_{R-C} = ((\pi^R_{SC} - \pi^C_{SC})/(\pi^C_{SC}))% )</td>
<td>( \Delta_{R-D} = ((\pi^R_{SC} - \pi^D_{SC})/(\pi^D_{SC}))% )</td>
</tr>
</tbody>
</table>

Table I. The comparison of three models under randomly fluctuating cassava market price and low- and high-yield uncertainty risk environment
5. Discussions and conclusion
To increase the production of cassava-based bioethanol to achieve the sustainable development of China, increasing the supply of cassava is the first step. In this paper, we investigate the decision-making behavior of a bioethanol production company and cassava planting farmers on the cooperation of contract farming scheme for the supply of cassava and production of bioethanol. Two decision models, namely, centralized model and decentralized model, are first analyzed as the baselines for the supply chain. Then, taking the real practices and characteristics of contract farming scheme into consideration, a risk-sharing model is proposed to coordinate the decision-making behavior of the players in the cassava-based bioethanol supply chain. Moreover, the effects of yield uncertainty risk, different risk-sharing coefficients and randomly fluctuating cassava market price on the optimal decisions and profits are analyzed. To show the advantage and feasibility of the proposed risk-sharing model, the decisions and profits derived using the proposed risk-sharing model are compared with those derived using the centralized and decentralized models.

The results reveal that the proposed risk-sharing model does help to mitigate the yield uncertainty risk and improve the resiliency of cassava-based bioethanol supply chain under yield and demand uncertainty environment in various ways listed as follows. First, it helps to encourage the farmers and the company to increase the input quantity and order quantity of cassava compared to a decentralized model. Though the proposed risk-sharing model cannot realize the supply chain coordination perfectly and achieve the supply chain performance in the centralized model, it is more maneuverable in production practice. Second, a proper setting for the risk-sharing coefficients combination can realize the Pareto improvement for both players. We found that either the company or the farmers’ profit might be worse off under unsuitable compensation and penalty prices setting compared to those of the decentralized model. But the profit of the whole supply chain can be improved through the risk-sharing model despite the setting of risk-sharing coefficients combination. And with proper risk-sharing coefficients, both farmers and the company’s profit will be improved. The proper setting of the risk-sharing coefficients combination can be bargained by the supply chain players depending on their bargaining powers. Third, the improvement of the proposed risk-sharing model will be larger as the yield uncertainty risk gets higher, and the supply chain performance of the risk-sharing model gets closer to that of the centralized model as the yield uncertainty risk gets higher. It is proved that the proposed model is able to improve the anti-risk ability of the system and reduce the influence of yield uncertainty.

Findings in this research have some reference value to China’s biomass energy market. Though the potential biomass resources are rich in China, the scattered layout of these resources, imperfect supply and marketing channels, and non-active participation of farmers directly caused the insufficient supply of the feedstock and limited production capability of the company. The proposed risk-sharing model, which is practicable in this supply chain, can not only motivate more farmers to participate in this industry to improve the supply of feedstock, but also help build a robust system to eliminate the potential uncertainty and get higher supply chain performance. Besides, considering the relationship between the proper risk-sharing coefficients and the player’s bargaining power, it is meaningful to help improve the bargaining power of the farmers because of their weakness in the supply chain. On the one side, agricultural cooperatives and family farms can be good representatives for farmers to negotiate with the company because they control the majority of feedstock resources and will seek benefits for farmers. On the other side, the bioethanol will become an important energy for China in the future. It is important to design an effective subsidy mechanism to promote the sustainable development of bioethanol industry. Improving farmers’ bargaining power will greatly motivate their enthusiasm and help balance the profit distribution of the supply chain.
Despite its major contributions, there are some limitations in this study. First, to ease the computational burden, we assume all farmers are homogeneous and do not have capacity constraints. In real world, however, the farmers might be heterogeneous in terms of cost structure and capacity level. Second, because of the uncertainty of natural disasters and weak bargaining power, the small-scale farmers tend to avoid risk in practice. But we assume that all farmers are risk-neutral in our study. Third, the discussion is based on the empirical analysis. Both yield and demand uncertainty are considered in this study, which makes it difficult to provide analytic solutions to the model and give proper risk-sharing coefficients.

Considering these limitations and production practice in China, several aspects of the present study will need further research. First, heterogeneous small-scale farmers with capacity constraint can be considered in the contract farming supply chain. Second, to avoid potential risks and pursue the optimal utility in the contract, farmers would prefer to behave risk-aversion rather than risk-neutral in production practice. Farmers’ risk preference will weaken the incentive to the company’s risk-sharing coefficient, which will finally affect the supply chain’s expected profit distribution between farmers and company. Third, as a kind of non-edible feedstock-based bioethanol, the cassava-based bioethanol has a great potential to get the government’s preferential policy in this industry. Hence, it would be of interest to investigate how to get the optimal government’s subsidy and how to set subsidized objects (farmers or company) for the cassava-based bioethanol supply chain from a government’s perspective. Last but not least, a key issue in contract farming is that farmers are often lack of enough capital, thus incorporating supply chain financing problems in farming supply chain in the model would help generate more interesting findings.

Note

1. Contract farming scheme is defined as “a system for the production and supply of agricultural produce under forward contracts with the essence of such contracts being a commitment to provide an agricultural commodity of a type, at a time and price, and in the quantity required by a known buyer” (Singh, 2002, p. 1621).

References


**Further reading**


**Appendix**

**Proof of Theorem 1:**

The supply chain’s profit under the centralized model is:

\[
E[\pi_{SC}(q^C, Q^C)] = P \cdot E_x [\min\{q^C \cdot v\}] + s_2 \cdot E_x \left[(q^C \cdot v - x)^+ + s_1 \cdot E_x \left[\left(nQ^C \cdot \mu - q^C\right)^+\right] - C_e \cdot E_x \left[(q^C - nQ^C \cdot \mu)^+\right] - nCQ^C - yq^C \cdot v\right]
\]

\[
= P \cdot \left[x - \int_{q^C}^{\infty} (x - q^C \cdot v) g(x) dx\right] + s_2 \cdot \int_{0}^{q^C} (q^C \cdot v - x) g(x) dx + s_1 \cdot \int_{q^C}^{\infty} (nQ^C \cdot (q^C - \mu)^+ f(\mu) d(\mu) - C_e - \int_{q^C}^{\infty} \left(q^C - nQ^C \cdot \mu\right) f(\mu) d(\mu) - nCQ^C - yq^C \cdot v\right].
\]
Hence, we have:

\[ \frac{\partial \pi_{SC}^C}{\partial Q^C} = n_s \pi + (C_s - s_1) \cdot \int_0^{q^C/nQ^C} n \mu f(\mu)d(\mu) - nC \]

\[ \frac{\partial \pi_{SC}^C}{\partial q^C} = P \cdot \int_{q^C/nQ^C}^{\infty} v g(x) d(x) + s_2 \cdot \int_0^{q^C/nQ^C} v g(x) d(x) - s_1 \int_{q^C/nQ^C}^{\infty} v f(\mu)d(\mu) - C_e \]

\[ \times \int_0^{q^C/nQ^C} v f(\mu)d(\mu) = v. \]

And:

\[ A = \frac{\partial^2 \pi_{SC}^C}{\partial (Q^C)^2} = -(C_s - s_1) \cdot \frac{(q^C)^2}{n(Q^C)^2} f\left(\frac{q^C}{nQ^C}\right), \]

\[ B = \frac{\partial^2 \pi_{SC}^C}{\partial (Q^C)\partial q^C} = -(P - s_2) v^2 g(q^C) - (C_e - s_1) \frac{1}{nQ^C} f\left(\frac{q^C}{nQ^C}\right), \]

\[ C = \frac{\partial^2 \pi_{SC}^C}{\partial q^C} = (C_e - s_1) \cdot \frac{q^C}{n(Q^C)^2} f\left(\frac{q^C}{nQ^C}\right). \]

For \((C_s - s_1) > 0\) and \((P - s_2) > 0\), we know that \(A < 0\), \(B < 0\) and \(C < 0\). Besides:

\[ AB - C^2 = (C_e - s_1) \cdot \frac{(q^C)^2}{(Q^C)^2} f\left(\frac{q^C}{nQ^C}\right) \cdot (P - s_2) v^2 g(q^C) > 0. \]

Therefore, \(\pi_{SC}^C\) is a concave function of \(Q^C\) and \(q^C\). Let \(\left(\frac{\partial \pi_{SC}^C}{\partial Q^C}\right) = 0\) and \(\left(\frac{\partial \pi_{SC}^C}{\partial q^C}\right) = 0\), we have Theorem 1.

Proof of Theorems 2 and 3:

The farmers’ expected profit under decentralized model is:

\[ E[\pi_F^D] = \omega \cdot E_{\mu} \left[ \min \left\{ n \mu Q^D, q^D \right\} \right] + s_1 E_{\mu} \left[ \left( n \mu Q^D - q^D \right)^+ \right] - nCQ^D \]

\[ = \omega \cdot \left[ q^D - \int_0^{nQ^D/nQ^D} q^D - nQ^D \mu f(\mu)d(\mu) \right] + s_1 \int_0^{\infty} \left( n \mu Q^D - q^D \right) f(\mu)d(\mu) - nCQ^D. \]

Hence, we have:

\[ \frac{\partial \pi_F^D}{\partial Q^D} = (\omega - s_1) \cdot \int_0^{nQ^D/nQ^D} n \mu f(\mu)d(\mu) + n \pi - nC, \]

\[ \frac{\partial^2 \pi_F^D}{\partial (Q^D)^2} = -(\omega - s_1) \cdot \frac{(q^D)^2}{n(Q^D)^2} f\left(\frac{q^D}{nQ^D}\right) < 0 \text{ for } \omega > s_1. \]

Therefore, \(\pi_F^D\) is a concave function of \(Q^D\). Let \(\left(\frac{\partial \pi_F^D}{\partial Q^D}\right) = 0\), the optimal input quantity satisfies \(\int_0^{q^D} \mu f(\mu)d\mu = (C_s - \pi/\omega - s_1). \)
For $Q^D = M_1 q^D$. We replace $M_1 = (q^D / q^P)$ into the company’s expected profit:

\[
E[\pi_E^D] = P \cdot E_x [\min\{x, q^D\}] - C_v E_v \left[\left(q^D z z - n q^D \mu\right)^+\right] \\
- \omega \cdot E_v \left[\min\{n Q^P \mu, q^P\}\right] + s_2 \cdot E_x \left[(q^D - x)^+\right] - y q^D v
\]

\[
= P \left[\bar{x} - \int_{q^D}^{\infty} (x-q^D)g(x)d(x)\right] - C_v \int_0^{1/nM_1} (q^D - n M_1 q^D \mu)f(\mu)d(\mu) \\
- \omega \cdot \left[q^D - \int_0^{1/nM_1} (q^D - n M_1 q^D \mu)f(\mu)d(\mu)\right] + s_2 \int_0^{q^D} (q^D - x)g(x)d(x) - y v.
\]

And:

\[
\frac{\partial \pi_E^D}{\partial q^P} = (P-s_2) \int_{q^D}^{\infty} v g(x)d(x) + s_2 v - y v - \omega + (\omega-C_v) \int_0^{1/nM_1} (1-n M_1 \mu)f(\mu)d(\mu),
\]

\[
\frac{\partial^2 \pi_E^D}{\partial (q^D)^2} = -(P-s_2)v^2 g(x) < 0 \text{ (for } P-s_2 > 0).\]

Therefore, $\pi_E^D$ is a concave function of $q^P$. Let $(\partial^2 \pi_E^D / \partial q^P) = 0$, the optimal-order quantity satisfies

\[
\int_{q^D}^{\infty} g(x)dx = ((\omega-(\omega-C_v)) \int_0^{1/nM_1} (1-n M_1 \mu)f(\mu)d(\mu) + y v - s_2 v) / ((P-s_2)v)).
\]

Proof of Theorems 4 and 5: similar to the proof of Theorems 2 and 3.

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Strategies and effective decision-making against terrorism affecting supply chain risk management and security

A novel combination of triangulated methods

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Abstract

Purpose – The purpose of this paper is to investigate the knowledge gaps in the published research on terrorism-related risk in supply chains, and to develop a framework of strategies and effective decision-making to enable practitioners to address terrorism-related risks in supply chain risk management (SCRM) and security.

Design/methodology/approach – The study adopts a novel combination of triangulated methods comprising a systematic literature review (SLR), text mining and network analysis. These methods have not been jointly utilized in past studies, and the approach constitutes a rigorous methodology that cross-validates results and ensures the reliability and validity of qualitative data.

Findings – The study reveals a number of key themes in the field of SCRM and security linked with terrorism. The authors identify relevant mitigation strategies and practices for effective strategic decision making. This subsequently leads us to develop a strategic framework of strategies and effective decision-making practices to address terrorism-related risk, affecting SCRM and security. The authors also identify key knowledge gaps in the literature and explore the main contributions by disciplines (e.g. business schools, engineering and maritime institutions) and countries.

Practical implications – The authors provide a strategic framework of strategies and effective decision-making practices that managers can use to minimize terrorism-related risk in the context of SCRM and security.

Originality/value – This paper introduces a novel methodological combination for improving the quality of SLRs. It uses the approach to systematically review the strategies and effective decision-making practices interlinked with terrorism risk, affecting SCRM and security. It identifies significant knowledge gaps and defines directions for future research.

Keywords Effective decision-making, Mitigation strategies, Novel combination of triangulated methods, Supply chain risk management and security, Terrorism risk

Paper type Research paper

Introduction

Terrorism is among the top five factors affecting supply chain risk management (SCRM) and security (World Economic Forum, 2013). Global supply chains and logistical infrastructures are particularly vulnerable to disruption due to their scope, scale and complexity (Stecke and Kumar, 2009). The British Standards Institute (2017) reported that terrorist attacks on international trade and supply chains increased by 16 percent between 2016 and 2017. In 2016 alone, a total of 346 attacks took place on supply chains, averaging at
The literature highlights the direct and indirect effects of terrorism on the cost and performance of global supply chains (Thissen, 2004). The costs of securing global supply chains vary with the amount of global trade utilized by particular international firms. The supply chain costs triggered by terrorism stem not only from securing the transportation of goods, but also from the need to underwrite the risk of delay or disruption of global supply chains. Examples of cost escalation include the potential for terrorist attacks to increase the cost of contracts due to the requirement for specialized security measures, high insurance premiums, and the need to conform to evolving counterterrorism regulations (MacPherson, 2008). Global supply chains incurred an extra $56bn worth of combined costs due to terrorist threats, extreme events, the migrant crisis and crime (Marle, 2016). These implications and impacts of terrorism on SCRM and security clearly demonstrate the significance of the topic and the need for systematic research studies to provide effective strategies and basis for decision-making to counter terrorism risks affecting supply chain security (Markmann et al., 2013; Shan and Zhuang, 2014; Ni et al., 2016).

Our initial review of the literature on terrorism-related risk in SCRM and security identifies the following major gaps. First, although several authors have carried out literature reviews on SCRM at various stages over the last 15 years, there is no systemic literature review on terrorism risk and its links with SCRM and security. Second, whilst the frequency of terrorist attacks and associated threats to global supply chains is increasing, existing strategies and relevant decision-making frameworks to address the risk arising from terrorism are inadequate and have not been systematically investigated (Markmann et al., 2013; Ni et al., 2016). Additionally, although a few studies provide some guidelines (Sheffi, 2001; Nurthen, 2003; Bueno-Solano and Cedillo-Campos, 2014; Shan and Zhuang, 2014), the contributions to the topic by different academic disciplines and countries have not been systematically categorized in order to explore differences in academic perspectives or the peculiarities of contextual settings.

In order to address these gaps, this paper seeks to advance our understanding of the terrorism-related risks affecting SCRM and security, providing key insights for developing strategies and effective decision-making to counter the impact of terrorism on supply chains. In carrying out the review and analyzing the data, our contributions are as follows: first, we identify developments in the research on terrorism risk in the context of SCRM and security and develop a strategic framework to help practitioners in strategic decision making to counter the impact of terrorism on supply chain performance and security. The framework encompasses three key components: terrorism risk management strategies, effective decision-making practices and SCRM and security. Second, we identify the knowledge gaps and categorize the key contributions to the topic from different disciplines (e.g. business schools, engineering and maritime institutes) and countries. Lastly, we introduce a novel combination of rigorous triangulation methods (a systematic review with text mining and network analysis) for cross-validating findings and ensuring the reliability and validity of data.

The paper is structured as follows. The next section provides a context for our study. Subsequent section describes our methodology, followed by the results of our systematic literature review (SLR) and framework development. We then identify the knowledge gaps in the extant literature and discuss our contributions to the field. The final section concludes with proposed directions for future research.

Context for the study
Terrorism and supply chain risk
Defining terrorism is not a simple matter: there is no single internationally accepted definition of what represents terrorism and the terrorism literature abounds with competing
definitions and typologies (Hyslop and Morgan, 2014). More than 100 definitions of terrorism were provided by various writers between 1936 and 1981, while Simon (1994) reported 212 different definitions of terrorism. Terrorism is the threat or actual use of force or violence to attain a political goal through fear, coercion, or intimidation (Alexander et al., 1979, p. 4). United Nations (1999) defines it as criminal acts intended or calculated to provoke a state of terror. According to Europol, terrorism is not an ideology or movement, it is a tactic or a method for attaining political goals (Europol, 2007, p. 9). Thus, individuals, groups and states can be involved in terrorism, depending on their intent to perpetrate criminal acts against people, areas and state (Locatelli, 2014). The lack of a universal definition is exemplified by the familiar comment that “one state’s terrorist is another state’s freedom fighter.” However, the definitions of terrorism converge around the notion that violence, or the threat of violence, is employed to frighten or intimidate people.

Li and Schaub (2004) studied international terrorist incidents in 112 countries from 1975 to 1997. They found that the Middle East had the highest percentage of international terrorist incidents and Europe ranked second. Africa, Asia, and the Americas suffered significantly fewer international terrorist attacks. However, there has been an escalation in international concern with the level of the global terrorist threat in subsequent decades, notably since the 9/11 attack in 2001.

There is no consensus on the definition of supply chain risk (Diehl and Spinler, 2013) and supply chain researchers provide a variety of definitions (Wagner and Bode, 2007). Christopher and Lee (2004), assert that there is no exact definition of risk, but rather a list of possible risk sources. They define supply chain risk as the “effect of external events such as wars, strikes or terrorist attacks and the impact of changes in business strategy” (p. 388). Table I provides a summary of key definitions.

Zsidisin et al. (2005) define supply chain risk as the product of two separate but interrelated elements: uncertainty and impact. There are two features of uncertainty that are linked to viability and supply chain continuity. The first is the lack of awareness of all the events that might occur and cause disruption for supply chain players. The second is the probability of occurrence of these events and its impact that deals with the potential costs generated by the events. Terrorism-related risks can have severe impacts in terms of magnitude on the area of their occurrence and are relatively unpredictable (Kleindorfer and Saad, 2005). In this study, the researchers examine supply chain risks related to the external environment and their sources at the country level by considering the macroeconomic environment and terrorism risk.

The concept of terrorism-related risk in SCRM became prominent in the literature in 2001 (Zegordi and Davarzani, 2012). Whilst there is extensive literature available on SCRM, supply chain disruption and supply chain security, only a limited number of studies deal with terrorism-related SCRM and how to secure supply chain activities from terrorist attacks (Sheffi, 2001). A few researchers have conducted studies on terrorism-related risks

<table>
<thead>
<tr>
<th>Authors</th>
<th>Definitions of supply chain risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>March and Shapira (1987, p. 1404)</td>
<td>Variation in the distribution of possible supply chain outcomes, their likelihood and their subjective values</td>
</tr>
<tr>
<td>Jütter et al. (2003, p. 7)</td>
<td>Any risks for the information, material and product flows from original supplier to the delivery of the final product for the end user</td>
</tr>
<tr>
<td>Wagner and Bode (2007, p. 303)</td>
<td>Risk as the negative deviation from the expected value of a certain performance measure, resulting in negative consequences for the focal firm</td>
</tr>
<tr>
<td>Manuj and Mentzer (2008, p. 197)</td>
<td>The distribution of performance outcomes of interest expressed in terms of losses, probability, speed of event, speed of losses, the time for detection of the events and frequency</td>
</tr>
</tbody>
</table>

Table I. Key definitions of supply chain risk
affecting different activities of supply chains such as supply chain logistics performance (Czinkota et al., 2005; Bueno-Solano and Cedillo-Campos, 2014), supply chain security performance (Sheffi, 2001; Thibault et al., 2006; MacPherson, 2008; Marlow, 2010; Reilly et al., 2012), supply chain resilience (Cox et al., 2011; Urciuoli et al., 2014), communication between supply chain partners after terrorist attacks (Degeneffe et al., 2009) and the impact of terrorism on employees working in those supply chains (Reade, 2009).

Similarly, while supply chain security is widely discussed in the supply chain risk literature, studies in the new supply chain security regulations due to terrorism-related risk and their impact on supply chain performance are limited (Sheu et al., 2006). Markmann et al. (2013) analyzed the influence of terrorism-related risk on global supply chain security and other studies are related to specific sectors. For example, Barnes and Oloruntoba (2005) and Raymond (2006) examine the new security initiatives’ impact on the maritime supply chain. There are some studies on transportation security in the context of terrorism-related risk (Prentice, 2008; Ekwall, 2010; Reilly et al., 2012; Strandberg, 2013). Nganje et al. (2008) and Pinior et al. (2015) discussed food supply chain security and bio-terrorism. A few studies addressing supply chain disruption management in the context of terrorism-related risk (Stecke and Kumar, 2009; Knemeyer et al., 2009), include not only operations performance (Bueno-Solano and Cedillo-Campos, 2014; Kauppi et al., 2016), but also financial performance (MacPherson, 2008; Ni et al., 2016). Several studies have examined the relationships between government initiatives and security strategies and efforts to avoid terrorist threats (e.g. Sheu et al., 2006; Vance, 2008; Ni et al., 2016).

The rise of terrorism-related risk has motivated firms to develop long-term strategies for supply chain sustainability and risk management. This area of research is an emergent one and there is a need for more studies (Shan and Zhuang, 2014), particularly ones that rigorously explore extant theoretical aspects of terrorism risk and their impacts (Hong and Ng, 2010).

Our study makes a substantial contribution to this domain by mapping the literature on the impacts of terrorism-related risk on supply chains and explicitly defining the significant aspects covered in the specific content of relevant articles, and exploring the developments in this emerging knowledge domain (Shan and Zhuang, 2014).

Methodology – SLR, text mining and network analysis
In order to extract and analyze the large volume of information and data generated by the scientific community, we deployed a novel combination of SLR, text mining and network analysis. These methods enable us to systematically identify and select existing studies, evaluate them against set criteria and analyze them, producing valid results by limiting the research bias. The SLR approach used in this study consists of the following major steps.

Database and article selection
This study collected research articles and their related citation data from the EBSCO Host, Science Direct, Emerald Insight, Web of Science, Scopus, Summon (University of Hull) and ABI/INFORM. These are well-established databases and comprehensively cover scientific sources. To identify the relevant research articles, we first developed a basic set of keywords and their derivatives (e.g. terror*, supply chain) using guidelines from the literature (Tranfield et al., 2003). To begin with, ten articles (from highly cited journals) related to supply chain management and SCRM were reviewed to identify the initial list of keywords, alongside three brainstorming sessions conducted with three supply chain management academics and two supply chain practitioners. The five experts in supply chain risk were selected for their specialist knowledge of terrorism-related risk in global supply chains. This process delivered the set of initial keywords (and derivatives) used in the subsequent database search to harvest a further set of articles, which were used to generate a list of
additional keywords used with high frequency in this field. We subsequently refined these keywords with a set of three experts in order to validate our search. As a result, we identified the following set of keywords:

1. Terror* and Supply Chain Risk
2. Terror* and Supply Chain Disruption
3. Terror* and Supply Chain Vulnerability
4. Terror* and Supply Chain Uncertainty
5. Terror* and Supply Chain Resilience
6. Terror* and Logistics
7. Terror* and Transportation
8. Terror* and Maritime
9. Terror* and Strategic Decision-Making
10. Terror* and Supply Chain Security

A condition was imposed that these search strings had to be included within the title, abstract and/or keywords for a research paper to be considered. The asterisk (*) was also used to find related words (e.g. terrorism, terrorists related to terror*). In this process, we only considered peer-reviewed articles, written in English and published from 2001 to 2016. We selected 2001 as the start date because this was when the issue of terrorism in the context of supply chains was first introduced (Sheffi, 2001). This procedure reduced the bibliographic data to a manageable level: the initial search revealed 1,371 research papers. Following the deletion of duplicates, 801 research papers met the initial inclusion criteria.

Article evaluation and coding
We then evaluated each paper by screening its title, abstract and keywords. In this step, we set a series of inclusion and exclusion criteria to capture only those articles related to terrorism-related risk in the context of SCRM and security. Thus, generic supply chain studies on risk management or security were excluded from the initial data set, unless they also addressed terrorism and its related risks to SCRM and security. Figure 1 shows a decision tree for excluding papers at each stage. Furthermore, we excluded conference papers. The pre-defined selection criteria were then applied to the abstracts of the remaining 626 papers to identify articles that addressed terrorism-related risk and its effects on SCRM and security. The abstract review stage resulted in the exclusion of a further 315 articles. Finally, the full texts of the remaining 311 articles were reviewed and this resulted in the exclusion of a further 247 articles. Our systematic procedure eventually yielded 64 research articles that satisfied the complete set of predetermined inclusion criteria.

The 64-collected research articles were then coded in terms of general information (e.g. titles, authors’ names, year of publication and journal name) and additional categories (e.g. disciplines, research methods, university names, schools/departments/institutions, industries and focus of studies) were identified. In order to mitigate the risk of introducing a subjective bias, two experts were engaged in the process of compiling this database and the preliminary result of coding was then validated by the third expert. This process was repeated until a consensus was reached between the experts.

In order to use the computational power of text mining methods, the selected articles were imported into NVivo for cross-validation and to ensure that they specifically addressed terrorism-related risks in supply chain management and to determine the key themes they covered. Word clouds were used to visualize the focus of their content. Figure 2 shows an
example of such cross checks, mainly focusing on terrorism, security and SCRM. The analytics from this figure confirm the validity and reliability of the selection process in identifying a final set of articles focusing on the core area of interest for this study. It also ensured the validity and reliability of the final articles and their text selected for further analysis, covering the main purpose of this study. Interestingly, it also reveals certain themes that have low values of relative frequency, suggesting that these are under-explored and need further research.

Using the variable features and additional categories, we coded and prepared a separate data set for network analysis. This data set was prepared based on the final research articles stored in NVivo. The subsequent procedures allowed us to categories interesting and relevant papers for citation analysis. We then examined networks and their clusters, to identify the knowledge gaps and contributions from various disciplines and countries.
The combination of triangulated methods (SLR, text mining and network analysis) deployed in our study constitutes a methodological innovation in ensuring the cross-validation, reliability and validity of qualitative data reviewed (this particular combination has not been used in any preceding studies).

**Results and framework development**

The main purpose of this study is to explore the developments within the field and to develop a strategic framework, consisting of terrorism-related risk management (TRM) strategies, effective decision-making practices and SCRM and security. This section presents the descriptive results from the SLR, followed by the thematic analysis that underpins the development of our framework.

**Descriptive results and identification of knowledge gaps**

More than 20 relevant journals were identified from seven databases, with a total of 1,371 articles using the keyword search. Table II provides details. After excluding duplicated articles (570), 801 articles were utilized to apply the criteria set for this research. After all exclusions, a total of 64 articles remained for the final analysis. Of the 64 articles, 30 are published in transportation journals and the remaining articles appear in journals related to operations, production, disaster prevention, economics and management.

The articles were also analyzed with respect to the year of publication. As shown in Figure 3, this clearly reveals that the topic of terrorism-related risk in the supply chain context has been gaining increasing attention since 2001 particularly progressing from 2010. Of the 64 articles analyzed, 34 articles were published between 2010 and 2014.

Table III shows the profile of the terrorism-related risk literature, defined in terms of research methods, disciplines, the core focus of studies, geo-location-specific (centric) view of data and industry sectors.

The distribution of articles with respect to the type of research method is shown in the first column of Table III. More than half of the articles followed a qualitative methodology while 41 percent focused on quantitative methods. A few of the articles employed mixed techniques. Papers were classified as deploying a qualitative methodology if the research was based primarily on conceptual theories, or deployed methods such as Delphi analysis, focus groups, literature reviews and case studies. Papers classified as deploying quantitative methods

<table>
<thead>
<tr>
<th>Search Terms</th>
<th>EBSCO Host</th>
<th>Science Direct</th>
<th>Emerald Insight</th>
<th>Web Science</th>
<th>Summon</th>
<th>Scopus</th>
<th>ABI/ INFORM</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply chain disruption and terrorism</td>
<td>14 (2)</td>
<td>4 (1)</td>
<td>0</td>
<td>21 (3)</td>
<td>24 (6)</td>
<td>22 (4)</td>
<td>13 (2)</td>
<td>98 (18)</td>
</tr>
<tr>
<td>Supply chain risk and terrorism</td>
<td>28 (9)</td>
<td>5 (2)</td>
<td>10</td>
<td>40 (12)</td>
<td>38 (12)</td>
<td>48 (21)</td>
<td>17 (9)</td>
<td>186 (65)</td>
</tr>
<tr>
<td>Supply chain vulnerability and terrorism</td>
<td>1</td>
<td>2</td>
<td>4 (4)</td>
<td>11 (7)</td>
<td>10 (6)</td>
<td>17 (8)</td>
<td>5 (2)</td>
<td>50 (27)</td>
</tr>
<tr>
<td>Supply chain resilience and terrorism</td>
<td>1 (1)</td>
<td>1</td>
<td>3 (2)</td>
<td>5 (5)</td>
<td>4 (3)</td>
<td>6 (4)</td>
<td>3 (2)</td>
<td>23 (17)</td>
</tr>
<tr>
<td>Supply chain security and terrorism</td>
<td>6 (4)</td>
<td>4 (3)</td>
<td>7 (4)</td>
<td>33 (20)</td>
<td>65 (28)</td>
<td>45 (21)</td>
<td>26 (14)</td>
<td>186 (94)</td>
</tr>
<tr>
<td>Maritime and terrorism</td>
<td>0</td>
<td>17 (4)</td>
<td>4 (2)</td>
<td>6 (3)</td>
<td>13 (9)</td>
<td>74 (17)</td>
<td>13 (9)</td>
<td>127 (34)</td>
</tr>
<tr>
<td>Strategic DM and terrorism</td>
<td>4</td>
<td>2</td>
<td>5 (2)</td>
<td>8 (6)</td>
<td>23 (15)</td>
<td>19 (16)</td>
<td>14 (12)</td>
<td>75 (51)</td>
</tr>
<tr>
<td>Logistics and terrorism</td>
<td>14 (5)</td>
<td>3</td>
<td>15 (8)</td>
<td>19 (5)</td>
<td>122 (88)</td>
<td>32 (14)</td>
<td>16 (2)</td>
<td>221 (142)</td>
</tr>
<tr>
<td>Transportation and terrorism</td>
<td>34 (6)</td>
<td>5 (1)</td>
<td>16 (5)</td>
<td>5 (4)</td>
<td>136 (120)</td>
<td>85 (15)</td>
<td>124 (71)</td>
<td>405 (222)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>102 (27)</strong></td>
<td><strong>43 (11)</strong></td>
<td><strong>64 (27)</strong></td>
<td><strong>148 (65)</strong></td>
<td><strong>435 (207)</strong></td>
<td><strong>348 (110)</strong></td>
<td><strong>231 (123)</strong></td>
<td><strong>1,371 (570)</strong></td>
</tr>
</tbody>
</table>

Table II. The number of articles and duplicates in each database

IMDS 118,7
were based on surveys, simulation, mathematical modeling, descriptive analysis, and other data mining techniques: none of the studies used the combination of methods utilized in our current paper.

The second column shows that 67 percent of the articles focused on the discipline of supply chain security (maritime and land transportation), while others dealt with various aspects of SCRM; 23 percent of the papers discussed terrorism as a catastrophic risk factor in SCRM, 5 percent of the articles focused on food supply chain security in the face of terrorism-related disruption, 2 percent discussed strategies for effective communication between supply chains after terrorist attacks and 2 percent analyzed effects of terrorism-related risk on supply chain employees.
In the third column, we categorize our 64 sample articles according to the core focus of the papers. The majority (25 percent) of articles assessed terrorism risk and 20 percent suggested mitigation strategies, 23 percent of the articles analyzed the impact of security initiatives on the performance of businesses and ports, 12 percent of the articles assessed terrorism risk in the SCS context and fewer than 10 percent focused on catastrophic risk analysis, terrorism and privacy risk analysis, supply chain performance and shopping mall security.

The selected articles are also classified with respect to geographical scope, as shown in the fourth column (“centric view of data”) of Table III. The geographical analysis of the literature showed that the majority of the articles took a global view (45 percent), followed by ones focusing on North America (33 percent) and the USA (27 percent). A limited number of articles focused on Asian or European contexts. Only one article investigated terrorism-related risk in the context of an area that was itself endemically affected by terrorism (Sri Lanka), but many other areas that are highly affected by terrorism (such as Pakistan and Afghanistan) have not been explored: this omission clearly demonstrates an important knowledge gap that needs to be addressed by future research.

The main purpose of classifying articles with respect to industrial sectors was to establish the extent to which different terrorism risk management strategies and effective decision making have been evaluated empirically in particular sectors. The classification of articles with respect to industrial application is shown in the last column of Table III. Most of the articles focused on maritime (40 percent) and land transportation (11 percent) industries. This finding is not surprising given the fact that various components of transportation systems have been shown historically to be prone to attacks both in wars and by terrorists (broadly defined). The “General” category covers a mix of different industries and the corresponding articles either reported multiple case studies or presented interviews/surveys in various industries; 8 percent of the selected articles were focused on bio-terrorism-related risk in food supply, and our analysis suggests a lack of research on other aspects of terrorist impact on food logistics service providers and on other important sectors (e.g. energy logistics providers). In total, 37 percent of the articles do not entail industry-specific research. This finding highlights the need for future researchers to carry out a larger number of industry-specific studies on terrorism-related risk in diverse sectors.

With regard to methodological orientation of the papers analyzed we found an encouraging trend in the use of mixed methods in recent years. Figure 4 illustrates that the gap between the numbers of qualitative and quantitative studies has almost disappeared. Another interesting finding is that quantitative methods became increasingly popular in the period 2009–2012. It is possible that this trend may be associated with the improved analytical power associated with “Big Data” and the availability of emerging software tools that can be utilized for more rigorous combinations of research methods and techniques.
Terrorism risk, SCRM and strategic decision making (thematic analysis)
The thematic analysis shows that terrorism-related risk affects supply chains at all three decision levels (operational, tactical and strategic). The literature highlights the potential role of TRM strategies in reducing risk by utilizing tools for effective strategic decision-making in the supply chain management context (Navarrete and Esteban, 2016). However, Snyder et al. (2006) argued that once a disruption happens, there is very little recourse in relation to supply chain infrastructure because strategic decisions cannot be adjusted and implemented quickly enough. Hale and Moberg (2005) proposed a strategic decision-making model that utilizes location science to assist logistics managers to more efficiently develop a system of safe and secure locations for the storage of critical equipment and supplies under terrorism threats. Modarress et al. (2012) developed a strategic decision-making process for making strategic investments in maritime transportation supply chains to mitigate risks associated with terrorism. In the manufacturing sector Czinkota et al.’s (2005) study shows how managers can hold the ideal inventory level in face of terrorism-related disruption by determining the ideal balance between make and buy. Their study also assists managers’ strategic decisions regarding foreign market entries. In a similar vein Nejad and Kuzgunkaya (2014) developed a strategic decision-making model for supply chain resilience, incorporating strategic stock and reconfigurable back-up suppliers in disruptions due to terrorism. Das and Lashkari (2015) formulated a model-based strategic decision-making approach to create risk readiness and resilience in the face of terrorism-related and other risks to supply chain operations. A summary of key terrorism risk mitigation strategies proposed in the literature is presented in Table IV.

The thematic analysis reveals that almost 40 percent of the articles address the issue of effective decision-making in the face of terrorism-related risk. The articles are identified in Table V and their findings can be used effectively to inform managers in making...
decisions about current and prospective terrorism risks and their potential impact on supply chain revenue.

Effective SCRM and security are predicated on combining mitigation strategies for terrorism risk management with effective-decision making practices. The framework presented in Figure 5 captures the key factors and relationships derived from our detailed review and analysis of the literature summarized in Tables IV and V.

Network analysis, knowledge gaps and contributions
The results of our Citation Network Analysis are presented in Figure 6. The network shows the reviewed papers (depicted as nodes in the network) and their related citations (depicted as color-coded directed links/edges between nodes). The size of node and font represents the number of citations associated with each paper and the color of edges represents the source paper that is cited in the target paper. This reveals clusters of papers addressing particular topics in the research domain as summarized in the following paragraphs.
The most cited paper (Sheffi, 2001) first addressed the topic of terrorism risk in supply chain management. He discussed the supply chain investments and re-organization needed to prepare for terrorist attacks in terms of the challenges of dealing with the aftermath.

Certifications
The second most cited paper is by Sheu et al. (2006). They examined several cases to determine how certifications such as the Customs-Trade Partnership against Terrorism (C-TPAT) affect international supply chain collaborations. They found that four out five companies significantly benefited from them through border inspections, lower costs and higher customer satisfaction. The third most cited paper was by Thibault et al. (2006). Their findings suggested that the new supply chain security measures created stronger public–private collaborations. Ni et al. (2016) found that early adopters of C-TPAT were not driven by economic benefits but rather by the need to minimize their exposure to the risks associated with failing to satisfy the goals associated with C-TPAT.
Economic considerations and geography
Thissen (2004) examined the increase in transportation costs due to the indirect effects of terrorist attacks on transport infrastructure. He also developed an approach for government to find the most vulnerable economic links in the infrastructure network and proposed to use a spatially applied general equilibrium model in the new economic geography tradition to measure the indirect economic effects. Raymond (2006) found that there are inherent weaknesses existing in the maritime industry that can be exploited by terrorist groups with maritime capabilities to target supply chains linked with specific geographical areas. Knemeyer et al. (2009) developed a process to proactively plan for catastrophic risk events (i.e. terrorism) through an integration of diverse research streams linked to risk management. In addition, they proposed a process building upon a current risk analysis model by incorporating an innovative methodology adopted by the insurance industry to calculate the risk of multiple types of catastrophic events on key supply chain locations.

Identification and management of risks and threats
Ekwall (2012) analyzed the nature of four antagonistic threats (threats: theft, terrorism, smuggling and piracy) and concluded that antagonistic threats are wicked problems. Reade (2009) found that there is a statistically significant negative relationship between employees’ sensitivity to terrorism and employees’ attitudes toward the company, team and job. Markmann et al. (2013) quantified man-made risks in global supply chains and analyzed stakeholder perceptions and communication processes. Pero and Sudy (2014) developed an approach to support managers in selecting activities, methods, and technologies to increase supply chain security, without reducing its efficiency. Their approach consists of the following steps: first, the identification and assessment of threats along the supply chain. Second, the identification of weak points. Third, the identification, development and provision of suitable target processes that increase security without negatively affecting efficiency. Fourth, the evaluation of expected impacts of the identified target processes on supply chain security and efficiency. Last, the implementation and monitoring of performance of the identified target processes. Yang et al. (2014) introduced a novel fuzzy evidential reasoning approach for the quantitative analysis of port facility security assessments. They used the major key security performance indicators and identified current port facility and security assessment practices. Männistö et al. (2014) and Urciuoli et al. (2014) identified the most prominent potential security threats to supply chains as terrorism, piracy, and wars. They also discussed the comprehensiveness of the portfolio of strategies built by the EU to deal with scarcity issues. However, they found these approaches were not often coordinated with supply chain strategies.

The results of our network analysis shows a fragmentation of the literature in the domain and suggests the need for an integrative conceptual framework to define and articulate the relationship between SCRM strategies, terrorism risk management strategies and relevant decision-making strategies. Our framework (Figure 5), based on the results of the SLR and text mining, makes a significant contribution towards addressing this knowledge gap.

Contributions by disciplines and countries
The results of our analysis of the contributions by different disciplines and countries are depicted in Figures 7 and 8. We found that the largest cluster of contributions originated from business schools, mainly focusing on SCRM, supply chain security, maritime and food supply chains. The second largest contribution was from engineering schools. They emphasized energy supply chains, SCRM, transportation and supply chain security. The third largest cluster of contributions was from maritime departments, focusing on supply chain security in the maritime industry. The rest of the clusters comprised contributions from various social science disciplines, including economics, law, political science, geography, defense and strategic studies. They generally focused on supply chain security, food, energy and transportation industries.
It is notable that the main contributors (business schools, engineering and maritime institutes) historically are not specialised in combatting terrorism. This finding clearly highlights the need for future research to engage inter-disciplinary or transdisciplinary teams in order to develop a more complete and coherent understanding of terrorism-related risks for supply chain management. This is an important pre-requisite for enabling managers to devise appropriate strategies for addressing the factors that give rise to these risks, and for developing more resilient business and operational models to avoid or mitigate the impact of potential threats and risks associated with terrorist activity in their environment.

There is a view that universities should invest in institutions to address the roots of terrorism in their research and teaching, developing measures to counter terrorist activity and reduce or...
eliminate those factors that encourage terrorism. Such institutions would potentially have an important role in society by promoting peace and countering terrorism through education.

Our analysis of the countries that the research is based in shows that US universities comprise the largest cluster (40 percent of the total selected articles 64), followed by European universities (34 percent) with Asian institutions contributing only 7 articles. This is an important observation as the Asian, Middle Eastern and African countries are amongst those experiencing the highest levels of terrorist activity (British Standards Institute, 2017). It is possible that researchers from these countries are inhibited from researching or publishing on this issue due to security considerations and/or the fear of reprisal from powerful individuals/groups/countries. However, their absence constitutes an important knowledge gap as published accounts risk omitting critical contextual factors that shape the situated impact of terrorist activity on supply chains located in those countries.

Conclusions and future research
This study is the first to provide a systematic review on terrorism risk, decision-making practices and interlocking effects on SCRM and security. Our further contribution is in introducing a novel methodology combining SLR, text mining and network analysis to explore the knowledge gaps in the published research. The methodology enhances the rigor of our identification and exploration of the corpus of literature. By deploying our novel methodology to explore the published research on terrorism-related risk in the context of SCRM and security, our study makes a substantial contribution to this domain by mapping the literature on the impacts of terrorism-related risk on supply chains and explicitly defining the significant aspects covered in the specific content of relevant articles, and exploring the developments in this emerging knowledge domain.

Our analysis of the content of individual research papers identified clusters of papers dealing with particular aspects of risk and security, showing a fragmentation of the literature in the domain. To address the fragmentation, we developed an integrative conceptual framework to define and articulate the relationship between SCRM strategies, terrorism-risk management strategies and relevant decision-making strategies.

Our analysis highlights the need for future research to:

• engage inter-disciplinary or transdisciplinary teams in order to develop a more complete and coherent understanding of terrorism-related risks for supply chain management;
• develop more sector-specific studies and cover a greater diversity of sectors; and
• conduct more studies based in Asia, the Middle East and Africa (with increased participation of scholars and practitioners from those regions).

These are important pre-requisites for academics and practitioners active in this research domain for mitigating against academic, cultural and national biases. Incorporating these features will generate more robust research and enable managers to:

• devise appropriate strategies for addressing the entire range of factors that give rise to risks; and
• develop more resilient business and operational models to avoid or mitigate the impact of potential threats and risks associated with terrorist activity in their environment.

Finally, we detected a recent rise in the popularity of quantitative methods, and this suggests that there is a positive appetite in the research community to develop large-scale investigations to quantify the relationship between the types of terrorism risks and individual indicators of supply chain performance. This is particularly important for practitioners concerned with global data-rich supply chains in which data analytics can play an important role in identifying terrorism-related activities and their impact on SCRM.
References


Further reading


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Procurement risk management under uncertainty: a review

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Abstract
Purpose – The purpose of this paper is twofold, first providing researchers with an overview about the uncertainties occurred in procurement including applicable approaches for analyzing different uncertain scenarios, and second proposing directions to inspire future research by identifying research gaps.
Design/methodology/approach – Papers related to supply chain risk management and procurement risk management (PRM) from 1995–2017 in several major databases are extracted by keywords and then further filtered based on the relevance to the topic, number of citations and publication year. A total of over 156 papers are selected. Definitions and current approaches related to procurement risks management are reviewed.
Findings – Five main risks in procurement process are identified. Apart from summarizing current strategies, suggestions are provided to facilitate strategy selection to handle procurement risks. Seven major future challenges and implications related PRM and different uncertainties are also indicated in this paper.
Research limitations/implications – Procurement decisions making under uncertainty has attracted considerable attention from researchers and practitioners. Despite the increasing awareness for risk management for supply chain, no detail and holistic review paper studied on procurement uncertainty. Managing procurement risk not only need to mitigate the risk of price and lead time, but also need to have sophisticated analysis techniques in supply and demand uncertainty.
Originality/value – The contribution of this review paper is to discuss the implications of the research findings and provides insight about future research. A novel research framework is introduced as reference guide for researchers to apply innovative approach of operations research to resolve the procurements uncertainty problems.
Keywords Procurement, Risk management, Supply chain management, Literature review, Supply risk
Paper type Literature review

1. Introduction
Manufacturing industry nowadays has a very fierce competition and competes with price, quality and logistics (Roberta et al., 2014). To keep pace with the industry, many manufacturing companies begin to outsource the business which is not their core competency (Kremic et al., 2006). Indeed, the trend of outsourcing makes the supply chain more complex and hard to control. From a survey conducted by Computer Science Cooperation, there are about 43 percent of firms reporting that their companies are facing disruption risk (Tang, 2006a). Enterprises may face negative consequence of risk if they do not realize the impact and occurrence of the risk. Risk has been well defined as the variance of return in financial industry and risk can adversely affect the expected yield (Markowitz, 1952). Risk management is not only an important issue of financial industry and it also has a growing concern in supply chain management as uncertainty of the occurrence of an event in one function of supply chain can brings to undesirable chain effect for the supply chain network (Finch, 2004; Tummala and Schoenherr, 2011).

The importance of procurement in the supply chain can be also realized from the percentage of cost it takes in the industry. Maucher and Hofmann (2011) mentioned that the
material cost are at 45 percent in German automobile industry. Furthermore, price fluctuation may be difficult to predict. In addition, quality level of supply is important as defective items would cause larger lost and make buyers recall products if defects are discovered by the downstream partners. Therefore, when designing the optimal lot sizing policy, the existence of defective items should be considered as one source of the random yield factor. To mitigate the risk, Mahapatra et al. (2017) suggested to combine contract and open market to obtain the optimum procurement under the uncertain market price.

It is obvious that the optimal decision making in PRM under uncertainty should incorporate many potential risk sources, such as demand, price and supply yield. Scholars have done considerable research in this area. Martel et al. (1995) studied the problem of procurement planning over rolling planning horizons facing the stochastic demand. In face of uncertain demand and price in spot market, Seifert et al. (2004) tried to find the optimal order quantity from forward contract and spot market in a single period setting. In a single period setting, Federgruen and Yang (2008) developed a model to configure the supply base and figure out order allocation among suppliers in the presence of yield and demand uncertainties. However, before implementing PRM strategies, it is necessary to find out the source of uncertainty which leads to procurement risk. Procurement risk is predominantly reliant on the manager’s experience and intuition as there is no systematic way for them to classify the source of procurement risk and myopic risk management strategy is formulated once the unexpected risk occurred. Although there are several review papers in supply chain risk management, according to author’s knowledge, there is no review paper published in PRM. In this paper, the topology of the PRM is devised so as to help management to realize the source of uncertainty in the procurement process. The adverse consequence of procurement risk is come from ignoring the uncertainty or wrong estimation of impact due to the lack of risk management knowledge, this paper provides the body of knowledge about procurement risk for both practitioners and researchers. Section 1 provides a brief introduction about the background of PRM. Section 2 describes the review methodology which is mainly based on the seven steps of Comprehensive Literature Review (CLR) approach. Section 3 provides the overview of the PRM. Section 4 is about the classification of PRM. Section 5 shows PRM strategies and modeling method. The conclusion and future trend of research direction are shown in Section 6.

2. Review methodology
Review methodology is based on CLR (Onwuegbuzie and Freis, 2016) which is a methodology of literature review. A flow chart of literature search procedure is depicted in Figure 1 to provide a clear picture of the review process and results. The selected papers were mainly published within 1995–2017 and the main electronic database includes Science Direct, Emerald, Scopus and Google Scholar. The keywords used to retrieve the relevant papers include risk management, supply chain management, supply risk, procurement, contract and sourcing. The papers are further filtered based on the relevance to the topic, number of citations and publication year. As described in Figure 1, over 153 papers from various journals, such as European Journal of Operational Research, International Journal of Production Economics and Operations Research are selected.

3. Overview of PRM
In this section, a PRM classification is outlined and positioned within the supply chain risk management structure proposed by Tang (2006a) who defined Supply chain risk management as “the management of supply chain risk through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity.” Furthermore, common procurement risks are identified to set our review scope in Subsection 3.1. In Subsection 3.2, the procurement risks and the related approaches are presented.
3.1 Proposed definition of procurement risks
Procurement is a series of coordination process to obtain the resource including materials, skills, capabilities and facilities to undertake their core business activities (Turban et al., 2008). From the perspective of external resource management, procurement was defined as to obtain external sources for maintaining and managing a company’s activities at the most favorable conditions (Jessop, 1994). Although there is no specific definition on procurement risk, the grounded definition of supply risk is stated by Zsidisin (2003) as “the probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety.” Kraljic’s (1983) supply
matrix has categorized different types of purchased items by realizing the correlation between supply risk and profit impact so as to decide the appropriate procurement strategy. HP is pioneer in setting up PRM framework for measuring uncertainties of price, demand and availability by scenario analysis (Nagali et al., 2008). Having realized those uncertainties, the contract is set up and valued. Numerous researches have been undergone and various purchase portfolios by considering operational cost, product availability and demand information are formulated so as to have optimal control of supply or minimizing the risks or variance (Agrawal and Nahmias, 1997; Aouam et al., 2010; Arnold et al., 2009; Babich et al., 2011). According to the authors’ knowledge, there is no clear definition of PRM. With the aim of setting a review scope and better guiding scholars through the published articles related to PRM under uncertainty, we define PRM as follows:

PRM is the management of procurement risk through reducing the exposure and uncertainty in price, lead time and demand so as to ensure continue flow of supply (material, skills, capabilities, facilities) with minimum disruption.

Procurement risk is the probability of variance associated with supply disruption in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to the subsequent process in the supply chain operation. According to Chambers and Quiggin (2000), uncertainty is defined as a state of having limited knowledge to exactly describe an existing state or future outcome. It is measured by the assigned probabilities of each possible state or outcome. Uncertainty is the inability to predict the consequence or outcome of activity accurately (Milliken, 1987). Rao and Goldsby (2009) provided a comprehensive review about the definition of risk. Lowrance (1980) mentioned that risk is a measure of the probability and severity of adverse effects. Simon et al. (1997) realized that the likelihood of the occurrence of an uncertain event or set of circumstance that would have an adverse result on the achievement of activities. Holton entailed the exposure to the event and uncertainty of possible outcome. In general, when the organization cannot manage a variety of uncertainty and brings the adverse effect on the business, it can be regarded as risk.

Procurement is part of supply chain but the consequence of poor PRM can be similar or same as supply chain risk management. Authors attempt to differentiate procurement risk from supply chain risk as procurement risk concerns more about the risk related to supply discontinuity and the contract between the buying firm and suppliers. Wrong estimation of demand and poor coordination between internal customer and supply source are main source of procurement risk and procurement risk is also under the umbrella of supply chain risk. According to a grounded definition of supply risk by Zsidisin (2003), author attempts to define the following component of procurement risk which is exclude from source of supply risk. Risk from new product development problems, outbound logistics and finished product quality rather than incoming material quality is included in the classification of supply risk rather than procurement risk.

3.2 Procurement risks and related PRM approaches
Specifically, within today’s volatile and dynamic market, procurement is exposed to many kinds of uncertainties, such as variable lead time, uncertain demand and volatile price. Generally, these uncertainties and risks can be classified into two groups: operational risks and disruption risks. Operational risk is the potential loss due to the lack of good coordination of supply chain activities among different parties in supply chain. Disruption risk is mainly referred to the loss from unexpected event due to natural disaster, strike, political instability or malfunction of equipment (Kleindorfer and Saad, 2005). After a comprehensive review of literature paper, a summary about all possible procurement uncertainties is described in Table I.
Lots of risks have been studied by researchers over the years and a considerable amount of papers have been published. These papers generally deal with two kind of procurement: physical products and service subscription. As different purchasing categories require different types of procurement strategy, we focus on those common uncertainties existing in physical product purchasing, such as demand, price, lead time, yield and disruption risks. Furthermore, according to Tang (2006a), supply chain risk management has the following four parts: product management, supply management, demand management and information management. To further delineate the scope of our review, we expand Tang (2006a)’s supply chain risk management structure and put our PRM under supply management.

For the purpose of a thorough review, related databases and journals are searched from 1995 to 2017. Furthermore, the keywords include price uncertainty (or risk, volatile), demand uncertainty (or risk), yield uncertainty (or risk, random), lead time uncertainty (or risk, variable) and disruption risks and those terms are used to describe procurement risks. In order to make robust procurement decisions, buyers put several uncertainties under consideration. In fact, these uncertainties would not only affect the configuration of supply base, but also the lot sizing. Therefore, it is critical to identify the possible risks first and the suitable strategies are selected and adopted for PRM. Figure 2 illustrates the typical procurement risks and the related PRM approaches. For instance, supplier

<table>
<thead>
<tr>
<th>Operational risks</th>
<th>Disruption risks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertain supply yield; variable lead time</td>
<td>Information system disruption</td>
</tr>
<tr>
<td>Poor data reliability; low efficiency information system</td>
<td>Political unrest or warfare</td>
</tr>
<tr>
<td>Budget limitation; interest rate fluctuating</td>
<td>Extreme weather or fire</td>
</tr>
<tr>
<td>Wrong inventory record; fluctuating exchange rate</td>
<td>Legal risks</td>
</tr>
<tr>
<td>Uncertain demand; shortage of key employees</td>
<td>Supplier default</td>
</tr>
<tr>
<td>Uncertain price</td>
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Table I. Risks in procurement

Figure 2. Procurement risk management and related approaches
diversification can be used to control the risk of uncertain supply while backup supply channel can be used to deal with uncertain lead time and disruption. In the following subsections, in-depth study and developed models under these different risks are discussed.

4. Classification of PRM

In general, there are five main risks that occur in procurement process which are demand fluctuation, vague price information, unreliable yield uncertain lead time and disruption risks. To deal with the procurement risk, buyers may diversify the risk with multiple suppliers and purchase in multiple periods so as to enhance flexibility, adaptability and responsiveness to the business environment. Table II provides a general classification of procurement risk and the related research papers in particular type of risk.

4.1 Demand fluctuation

A lot of products’ demands are not stable, especially those high-tech and trendy products. Companies should be capable of dealing with the uncertainty of demand in order to survive. A considerable amount of research work has been done by scholars (e.g. Li and Wang, 2010; Choi and Ruszczyński, 2011; Seifert and Langenberg, 2011) in the past years. These research work and models are mostly developed under single period (one stage or two stages) or multi period. For one-stage decision making, it is often the case that buyer needs to design the procurement plan such as supply base configuration, lot sizing and forward contract selection before the demand is realized (e.g. Swaminathan and Shanthikumar, 1999; Zimberg and Testuri, 2006). While two-stage decision-making process divides the single period into two stages: the first stage is similar as one-stage model, and the second stage tries to figure out how many products need to be bought from spot market or via instance order after obtaining more accurate demand information (e.g. Burnetas and Gilbert, 2001; Erhun et al., 2008; Fu et al., 2010). The third type is those seeking the optimal solution for multiple periods (e.g. Martel et al., 1995; Bonser and Wu, 2001; Yan et al., 2003; Nagar and Jain, 2008). Comparing with the single period model, more research can be done for multiple period model as long-term inventory planning is important, thus making it impossible to directly extend single period conclusion into multiple periods.

Scholars have proposed several risk management approaches to handle demand risk. First, demand information is continuously updated so as to obtain a more accurate order quantity. Second, in order to reach the win-win solution, it is suggested to design the production and procurement plan together, or making integrated sourcing and inventory decision. The third approach is to have a backup supply channel. After demand has realized, buyer could place an instant order or purchase from spot market to meet demand. Fourth, demand uncertainty can be mitigated using financial products, for example, options and futures. Option contract is a useful tool to mitigate demand risk by giving buyers the right but not the obligation to execute the contract.

4.2 Vague price information

The price of raw materials and electrical components are not constant in the market. Another uncertain price scenario is when suppliers offer periodic price discount campaigns. In order to compete with other companies, buyers have to make better procurement decision underprice uncertainty, including the time to purchase and purchasing amount. Different purchasing time usually means different purchasing price and the inventory holding length, thus resulting in different level of costs. Das and Abdel-Malek (2003) suggested developing a flexible buyer–supplier relationship to reduce price uncertainty. Sun et al. (2010) proposed a two-stage fuzzy programming to model uncertain spot market price. Efforts to reduce price risk can be also found in Seifert et al. (2004), Spinler and Huchzermeier (2006) and Woo et al. (2006).
<table>
<thead>
<tr>
<th>Risks</th>
<th>Single channel and single period</th>
<th>Single channel and multiple periods</th>
<th>Multiple channels and single period</th>
<th>Multiple channels and multiple periods</th>
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<tr>
<td>Lead time</td>
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<tr>
<td>Disruption risks</td>
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<td>Multiple uncertainties</td>
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Reiner et al. (2014) developed a scenario-based multi-stage stochastic programming to minimize the expected procurement cost under various uncertain price event like price discount or a change in a price-index.

In order to handle price risk, three most commonly used strategies are as follows. First, different procurement time and quantity would affect the inventory holding cost and inventory level, so one way to reduce price risk is to integrate sourcing and inventory decision. Furthermore, flexible contract is also a useful method to mitigate price risk. An inflexible contract requires the buyer to determine not only the optimal quantity but also optimal purchasing time, while flexible contract usually gives buyer the freedom to collect items within a period. Last but not the least; with the continuous development of financial market, many items can be bought in the form of option contract or futures contract. These financial tools can also help to hedge price risk such as fluctuated exchange price. Liu and Nagurney (2011) has studied about how the competition intensity and exchange rate can affect the risk-neutral and risk-averse firm to allocate off-shore-outsourcing activities as international sourcing can help hedge the risk of exchange rate fluctuation (Lowe et al., 2002). In the findings of (Kim et al., 2006; Allayannis et al., 2001), it is realized that financial hedging is more effective compared with operational hedging.

4.3 Unreliable yield
Uncertain supply yield can come from a number of sources. For instance, because of the supplier’s limited production capability, they could not deliver all the products on time (Erdem and Özekici, 2002; Yang et al., 2007; Keren, 2009). Another situation is that not all the supplier’s products meet the requirement, so only a fraction of products can be further used (e.g. Agrawal and Nahmias, 1997; Bollapragada and Morton, 1999; Maddah et al., 2009). Maddah et al. (2009) studied a problem with two types of supplies: one is Type A which is of perfect quality but higher cost; while type B is the one with imperfect quality and lower cost. The classical single period (newsvendor) and economic order quantity model are extended by incorporating random supply and yield uncertainty in their work. After comparing with traditional models, only Type A product should be considered and the proposed model proves that accounting Type B would significantly increase profits. For more detail of yield uncertainty, readers can refer to Yano and Lee (1995) which is a comprehensive and excellent literature review of lot sizing under uncertainty. Besides, Chen and Tan (2016) studied the inventory model to show that the ordering policy will be relatively stable if there is only one Type A while the others are Type B.

Facing uncertain yield, two approaches are most widely used. First, supplier diversification is using multiple suppliers when the available suppliers are not reliable. This could help to reduce the yield uncertainty. Collaboration with supplier is another mechanism to minimize uncertain yield. Capital investment to improve production line or inspection center is an instance (Talluri et al., 2010).

4.4 Uncertain lead time
When buyer asks for quotation, supplier usually replies with price and lead time. If the uncertainty of lead time cannot be controlled properly, it would increase total cost and reduce customer service level. Conducting proper ways to control the uncertainty of lead time is important and necessary. Some of the following approaches are commonly used by buyers, such as deciding the optimal ordering time and using backup supply channel.

In fact, the variable lead time requires buyer to optimize and obtain the optimal ordering time decision. Hariga and Ben-Daya (1999) took the variable lead time and the partial lead time distributions into consideration, so as to determine the optimal reduction in procurement lead time distribution with optimal ordering policy. Hsu et al. (2007) also examined the effects of lead time uncertainty, product expiration date and capital limitation
for setting the ordering policy. The results showed that the retailer’s profit is highly influenced by the uncertain lead time and there should be compensation mechanism to enhance supplier collaboration.

There is another situation where component costs are too high to be kept as inventory. Therefore, many firms optimize the best ordering time with the distribution of lead time, expected holding and backlogging cost. Chauhan et al. (2009) investigated such a model and proposed an algorithm to solve it. Moreover, many firms begin to place orders overseas, which would bring low purchasing unit cost but would also increase lead time risk. However, from another perspective, a more accurate demand forecasting would help buyers to manage the lead time uncertainty. Wang and Tomlin (2009) studied how a firm continuously updated its demand during selling season and design the optimal procurement policy when facing lead time risk. The results showed that the firm became less sensitive to the lead time uncertainty as the demand forecast updating process becomes more efficient. Kouvelis and Li (2012) proposed two contingency strategies which are dynamic emergency response and disruption safety stock. Through the strategies, safety stock can be released appropriately when late delivery occurred and emergency order can be decided at the right time easily, as a result, the cost of handling uncertain lead time would be reduced.

4.5 Disruption risks
In the face of supplier disruption risk, buyer may configure the supply base with backup suppliers. However, a larger number of suppliers may result in higher cost. Therefore, it is important to find the optimal number of suppliers. Ruiz-Torres and Mahmoodi (2007) used decision tree to determine the number of suppliers. In fact, the model investigated two situations: same failure probability of each supplier or different failure probability of each supplier. The results showed that when the reliability of supplier is really high, sole supply strategy may be the optimal. But as the supplier becomes less reliable, additional suppliers may be needed to obtain the lowest cost. Meena et al. (2011) developed an algorithm to obtain the number of suppliers under catastrophic events disruption through considering the combination of failure rate, inefficient capacity and it is important to find the optimal solution for minimizing the total costs.

Regarding the supplier failure, most of the models assume that the failure probability of suppliers is independent. Actually this may not be true in all situations. Wagner et al. (2009) used copula functions to capture the default dependence between suppliers. Copula function is a way to represent joint distribution. An empirical data from automotive suppliers helped to illustrate the importance to investigate supplier default dependence in a supplier portfolio. Costantino and Pellegrino (2010) investigated both single and multiple sourcing when there is supplier default risk. Monte Carlo simulation model is adopted and the advantages of multiple sourcing in risky environments are examined. Silbermayr and Minner (2014) studied a buyer procures from multiple supplier who are having the risk of supply interruption, the author modeled a Semi-Markov decision process to show the benefit of multiple sourcing over single sourcing. The result provided an insight for the company to select multiple sourcing instead of single sourcing so as to reduce the risk of getting penalty. Later, Silbermayr and Minner (2016) investigated more about the optimal dual sourcing strategy on disruption risk reduction by considering the saving on procurement cost, improvement the learning rate and reduction of reliability, the optimal robust strategy can be set as 75:25 dual sourcing option.

4.6 Multiple uncertainties
Due to the current complex business environment, the above-mentioned risks would be interrelated, which cause a more destructive economic consequence. In addition, mistakenly identifying the risk causes the under-utilization of the regular supplier and over-utilization
of the backup supplier (Guo et al., 2016). In order to better address the supply chain risks, considering multiple uncertain factors would be more important. Li (2017) considers a company procures from two suppliers that are subjected to “all-or-nothing” disruption risk and random yield risk respectively, to fulfill its deterministic demand. The researcher conducts three models for the above scenarios including no resource and ordering resource from one suppliers. As a result, the author can determine which strategies including single sourcing and dual sourcing should be adopted for each scenario to obtain the optimal order quantity. Guo et al. (2016) studied the contingent capacity strategy when sourcing from a regular supplier having the above uncertainties with an uncertain demand, the author pointed out that the contingency planning of ordering quantity from regular supplier should be more than backup supplier if the overall supply risk remains unchanged.

Apart from considering disruption and yield risk, Shi et al. (2011) considered the uncertain demand and price in China market. The authors developed a portfolio procurement approach to alleviate the procurement risk using various procurement means including long-term contracts, spot procurements and option-based supply contracts. They constructed a multi-stage stochastic programming model to determine the effectiveness of implementing the portfolio approach along a time horizon. The result shows that the proposed portfolio approach performs well in terms of profit and procurement risk exposure. Hali (2013) also considered the uncertain demand and price with respect to the procurement, production and delivery planning. The author developed a stochastic chance constraint programming with PSO algorithm approach to minimize the cost. The result shows that applying multi-time periods integrated planning of supply chain can reduce the cost and make the decision effectively.

5. PRM strategies and modeling method
In order to explore the PRM from different point of view, the PRM structure in Figure 3 is proposed. First, as described in Section 1, buyers carefully review their purchasing requirement, whether it is cost sensitive or urgent. Different purchasing requirement may need totally different strategies. After understanding clearly about the requirements, it is then necessary to identify the procurement risks. In this paper, the various uncertainties existed in procurement are identified and examined in Sections 2 and 3, especially that the uncertain demand, price, yield, lead time and disruption risks are thoroughly investigated. These risks can be used as reference when buyers need to identify their own specific risks. In addition, this paper also provides a review of the latest strategy to deal with these uncertainties (Subsection 5.1–5.4). If the chosen strategy cannot fulfill the purchasing requirement, a second round of risk management analysis is needed. In the references of risk management, only a few strategies are commonly adopted. For instance, supplier diversification and utilization of financial products are widely adopted for mitigating demand uncertainty and backup sourcing is suitable for volatile lead time scenario. Hedging strategy is usually adopted to reduce price and demand uncertainty. Some specific methods are used to mitigate the lead time and disruption risks. Therefore, the following subsections would focus on discussing in detail about specific PRM methods.

5.1 Supplier diversification
Supplier diversification is one of the methods to mitigate risk and researchers have formulated models with objective mainly for minimizing the cost. Table III summarizes the findings in supplier diversification.

Facing uncertain yield, demand and price, buyers try to diversify their supply base in order to prepare for the risks, because small orders from a large number of suppliers can reduce yield uncertainty. On the other hand, the fixed cost with each supplier would increase the total cost, so diversification approach does not mean having as many suppliers as
Procurement Requirement Analysis
Business Requirements: Met 100% demand; Time urgency; Minimal Quality level; Flexible supply quantity

Procurement Risk Identification
Risk Factors: Demand risk; Price risk; Lead time risk; Yield risk; Exchange rate risk; Logistics risk; IT system risk; Disruption risk
Identification Methods: Risk Map; Risk Solver (Monte Carlo simulation); Failure Mode and Effects Analysis

Procurement Risk Evaluation
Evaluation Criteria: Maximum expected profit (with or without minimal demand fulfillment); Minimal total cost; Shortest lead time; Maximum or minimal utility function (e.g. Mean-variance framework)
Types of Modeling: Single period and single channel; Single period and multiple channels; Multiple period and single channel; Multiple period and multiple channels
Solution Techniques: Analytical procedure; Linear programming; Goal programming; Mixed integer programming; Dynamic programming; Monte-Carlo; Discrete-event; Simulated appealing; Genetic algorithm

Risk Management Strategies Selection
Uncertain Demand: Supplier diversification; Integrated decision making; Back up sourcing
Uncertain Price: Price hedging using options; Flexible contract
Uncertain Yield: Supplier diversification; Supplier development through capital investment
Uncertain Lead Time: Back up sourcing; Flexible contract
Disruption Risk: Back up sourcing

Solution Techniques: Analytical procedure; Linear programming; Goal programming; Mixed integer programming; Dynamic programming; Monte-Carlo; Discrete-event; Simulated appealing; Genetic algorithm

Types of Modeling: Single period and single channel; Single period and multiple channels; Multiple period and single channel; Multiple period and multiple channels

Evaluation Criteria: Maximum expected profit (with or without minimal demand fulfillment); Minimal total cost; Shortest lead time; Maximum or minimal utility function (e.g. Mean-variance framework)

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Uncertain Demand: Supplier diversification; Integrated decision making; Back up sourcing
Uncertain Price: Price hedging using options; Flexible contract
Uncertain Yield: Supplier diversification; Supplier development through capital investment
Uncertain Lead Time: Back up sourcing; Flexible contract
Disruption Risk: Back up sourcing

PRM under uncertainty: a review

Figure 3. Procurement risk management structure

Table III. An overview of procurement risk management models with supplier diversification strategy
possible and there is a tradeoff between the cost and supply continuity risk. Many scholars have studied this situation in single period setting. In the presence of uncertain supply yield, Agrawal and Nahmias (1997) adopted the strategy of using multiple suppliers and optimized the order policy. It is proved that receiving small orders from a large number of suppliers could help to reduce the random yield risk. Specifically, Agrawal and Nahmias (1997) examined how many suppliers are needed to be selected when the yield of each supplier’s products is different. By trying to order the optimal order quantity, they optimized the total profit:

\[
\text{Profit} = \text{Revenue} - \text{Purchasing Cost} - \text{Shortage Cost} - \text{Holding Cost} - \text{Fixed Cost}.
\]

The result shows that the optimal expected profit is concave in the number of suppliers \(n\). The concavity means the optimal solution exists. Under the assumption of no fixed cost, it is proved that the optimal profit is concavely increasing with the number of suppliers because the variance of yield decreases with \(n\). However, if there is a fixed cost, the optimal number of supplier is chosen to make the tradeoff between fixed costs and the benefit of supplier diversification. Swaminathan and Shanthikumar (1999) studied supplier diversification under demand uncertainty using both single period and multi-period models. Moreover, two types of suppliers are considered: one with high cost and high reliability while the other is offering low price. The reliability is also low and the expected cost is expressed with parameters of cost and demand. Fu et al. (2010) decided the sourcing quantity to be executed from the option contract. They first select a supply base which has the following characteristics. No particular option contract can dominate the other one in term of the reservation cost and holding costs. Otherwise, this kind of option contract will not be engaged in the market. A new concept of measuring the effects of portfolio is proposed by Fu et al. (2010):

\[
PE = \frac{C_s - C_m}{C_m}.
\]

\(PE\) is used to show the relative error of an optimal single contract cost \(C^*_s\) compared to the optimal portfolio procurement cost \(C^*_m\). In addition, a two-period model is also examined and optimal properties are discovered to show the effect of inventory. Their study also shows that correlation between demand and spot price can greatly affect the order decisions. In a high demand-spot price correlation environment, option contract plays a more important role in serving the demand. Unlike the previous papers which consider only cost, Zhang (2010) took the total purchase quantity attribute and service level attribute into account when designing the optimal procurement mechanism. It also pointed out that the optimal procurement plan consists of a list of nonlinear contracts with different quantity and service level. To further simplify the results, the value of the two attributes are checked and found to have different implications. Thus, a fixed level which consists of a target service level and price-quantity menu is proved to help buyer yield optimal profit. Zhang and Zhang (2010) tried to purchase products from a group of suppliers which quoted different prices and order restrictions (minimum and maximum order sizes). Purchasing and holding cost are also considered in the model. This problem is formulated as a mixed integer programming and solved with branch and bound algorithm. Hazra and Mahadevan (2009) conducted similar research, but the difference of Hazra and Mahadevan (2009) and Zhang and Zhang (2010) is that Hazra and Mahadevan (2009) adopted the equal allocation strategy among the suppliers. Closed-form analytical solutions are provided and the results provide the following managerial insight. It is better to have a pre-qualified supply base with greater capacity heterogeneity rather than simply increasing the number of suppliers.

To examine the effects of supplier diversification under uncertain supply, Federgruen and Yang have done a lot of contributions. Federgruen and Yang (2008) selected which suppliers to retain, and how much to order from which supplier. The objective is to minimize
the total procurement cost and meet the uncertain demand with a given probability. Two kinds of situations are considered. First, all the $n$ potential suppliers have same fixed cost and yield distribution. Secondly, under the general case that suppliers have different fixed costs and yield factor distributions, large-deviations technique and the central limit theorem based approximations are used to obtain the optimal solution. Federgruen and Yang (2009) made further contribution of supplier diversification by differentiating the service constraint model, where the delivered and usable units must cover the demand at a certain probability and the total cost model is set that the orders are determined so as to minimize the total cost. One of the most important contributions of this paper is to prove the difference of service constraint model and total cost model under multiple suppliers with unreliable yields. These two models are known to be the same with single and fully reliable supplier. To further analyze the utilization of supplier diversification strategy, Federgruen and Yang (2011) developed a model to find the optimal procurement decision under multiple periods. An important contribution of their paper is to propose a two-part fee structure paid to supplier $i$ in period $t$:

$$c_{it} = c^0_{it} + c^r_{it} \beta_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{2}$$

where $c^0_{it}$ is the price charged by supplier $i$ in period $t$ for every ordered unit and $c^r_{it}$ is the additional price charged by supplier $i$ in period $t$ for every effective unit delivered.

They developed an efficient algorithm and identified the optimal procurement strategy. For example, it is no longer optimal to use a base-stock policy in contrast to the classical model. Instead, it suggested retaining $k^*$ suppliers that are cheapest in terms of the effective cost rates. The value of $k^*$ depends on suppliers’ yield characteristics, demand distribution and cost parameters.

With the development of financial markets, another emerging direction of using supplier diversification is for mitigating uncertain price. Buyers may choose to buy some financial products to control risks, such as option contracts, futures and other derivatives. Woo et al. (2006) used the case of a local distribution company to explain how to determine the extent to which it should rely on spot markets, forward contracts and long-term tolling agreement. The result showed that efficient frontier is a useful decision-making tool. An alternative dynamic strategy models the problem as a mean-risk stochastic problem which is proved to be better comparing with the naïve strategy. Rocha and Kuhn (2012) also used the mean-variance optimization model for the management of electricity procurement from spot market and other financial derivatives. By aggregating periods into macro periods and restricting the decision rules to those affined in the history of the risk factors, the complex multiple stage model is converted into a tractable quadratic program. The numerical experiments highlighted the superiority of LDR method in enabling scalability for multiple stage models.

5.2 Backup sourcing with information updating

Backup sourcing is a commonly used strategy to meet customer’s uncertain demand. As demand information is not accurate until the selling season approaches, it is quite common for buyers to have backup sourcing with demand information updating. Table IV shows the overview of PRM model with backup sourcing strategy.

The benefit of information updating is also examined by Yan et al. (2003) and it is modeled in a dual supply mode. There exists two suppliers with unit cost $c_i$ and lead time $L_i, i = 1, 2$, where $c_1 < c_2$ and $L_2 < L_1$. This means the convenience of using a supplier with short lead time always goes along with paying for a high unit price. An initial order can be given to the low cost but slow supplier; and reactive supply can be ordered from the relatively high cost and fast suppliers to meet demand. The obtained analytical optimal order solutions are validated and tested by purchasing micro-controller by an industrial company.
Another most commonly studied problem is to try to determine the optimal procurement quantity at the beginning of the ordering stage and the amount to order from backup sourcing channel during the selling season. To have a quick response to the urgent demand, backup sourcing supplier tends to offer a very short lead time to buyers. At the same time, the price of products from backup supplier is higher compared with other suppliers who have a relatively longer lead time. Within the single channel and single period setting, Hariga and Ben-Daya (1999) studied the optimal ordering decisions making with the reduction of procurement lead time duration in complete and partial lead time demand distributions. After observing that the price of some short life cycle product increases as the selling season advances, Burnetas and Gilbert (2001) made the decision whether to pay low price when demand information is limited or pay a higher price when demand information is more accurate. This problem is examined under both single period and multiple periods. Chen et al. (2006) developed a model so that the manufacturer determines the production quantity in the first stage when there is limited information about the demand. In the second stage, when demand information is more accurate, the buyer specified his order quantity. A risk sharing contract is proposed to promote the coordination between the manufacturer and the buyer. When facing uncertainties resulted from both demand and yield, Mukhopadhyay and Ma (2009) developed a model and made the optimal procurement decision under different amount of information situations about the yield rate. Similarly, the problem considered by Arnold et al. (2009) also tried to solve more than one risk factor: namely uncertain demand and purchasing cost. All these efforts would help companies to reduce hidden cost in the dynamic business environment. Sting and Huchzermeier (2010) studied a case with one overseas supplier and one backup supplier. The shortages of overseas supplier are the lack of reliability and flexibility. A backup supplier can help to improve the responsiveness. Xu et al. (2010) had a totally different assumption of whether overseas supplier is reliable or not. They considered to source from two urgent supply options rather than from the long lead time overseas supplier. The overseas supplier is prime and the product’s quality is good, whereas the urgent supplier’s products are inferior in quality and expensive. The contribution of their paper is to adopt Stackelberge game model to evaluate the involvement of two urgent backup supply: the common price-only contract, and a contract menu consisting of a transfer payment and a lead time quotation \((L, T)\). Furthermore, with sensitivity analysis, it is found that \((L, T)\) contract has higher advantages over the common price-only contract when the market acceptance of substitutable modules and the uncertain nature of urgent supplier are high. Some prime suppliers can also offer

<table>
<thead>
<tr>
<th>Reference</th>
<th>Demand</th>
<th>Price</th>
<th>Yield</th>
<th>Lead Time</th>
<th>Disruption</th>
<th>Correlation</th>
<th>Objective</th>
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<tbody>
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<td>Fixed</td>
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<td>×</td>
<td>×</td>
<td>×</td>
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<td>Sting and Huchzermeier (2010)</td>
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<td>Minimize cost</td>
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<td>Variable</td>
<td>×</td>
<td>×</td>
<td>Minimize cost</td>
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<tr>
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<td>Minimize cost</td>
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<td>Qi (2013)</td>
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<td>Minimize cost</td>
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<tr>
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<td>×</td>
<td>Yes</td>
<td>×</td>
<td>Minimize cost</td>
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<tr>
<td>Silbermayr and Minner (2014)</td>
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<td>Random</td>
<td>×</td>
<td>Random</td>
<td>Yes</td>
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<td>Minimize cost</td>
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</table>

Table IV. An overview of procurement risk management models with backup sourcing strategy.
instance orders. Instead of finding multiple backup sourcing channels, some of the buyers obtain the benefits from the same prime supplier. Li et al. (2011) considered how to place both initial order and supplementary order in a multi-period situation. The uniqueness of Nash equilibrium is proved and closed-form Nash equilibrium solution is found when parameters are stationary. The numerical study shows the backup order option is beneficial for the following scenarios: lower cost, lower value, lower inventory cost of supplier, higher inventory cost of buyer and higher demand variation.

With the development of financial markets, a lot of industry professionals and researchers try to protect company from risks by tapping into these products. Seifert et al. (2004) studied the usage of spot market for meeting customer’s demand. They analyzed and compared four procurement scenarios: pure contract sourcing, contract sourcing with buying only from spot market, contract sourcing with selling only from spot market; spot market buying and selling. Demand and spot price are modeled as bivariate normal distribution. The proposed objective function for both buying and selling is to minimize the utility function \(Z(Q):\)

\[
Z(Q) = E(q) - kVar(q), \quad \text{where } k > 0.
\]  

After deriving the equation of expected profit \(E(q)\) and profit variance \(Var(q)\), buyer links them to form a comprehensive evaluation measure by the risk aversion \(k\) of the buyer. The analytical form of procurement quantity from contract supplier is discovered. The result tells us that the optimal order quantity is positively related to the mean of demand and spot price, while it has a negative relationship with risk aversion parameter, demand standard deviation. This means that backup sourcing is more important when market is not stable and buyer is much more risk averse. Similarly, Fu et al. (2010) also suggested buyers to use spot market. Furthermore, they also used a portfolio of option contract to reduce risks. The option contracts enable buyers to hedge the risk of volatile price and uncertain demand. Different from other studies, the authors studied the correlation of demand and spot price, the procurement cost is inversely proportional to the volatility of spot price and it is found that two suppliers is effective enough to have nearly-optimal performance.

The adoption of backup supplier is also a useful method to deal with lead time uncertainty. Kouvelis and Li (2008) examined when and how many to order from a backup supplier to minimize the total cost. The benefits of using flexible backup supplier in the form of dual sourcing are investigated using numerical analysis.

### 5.3 Integrated sourcing and production decision making

Coordination is another approach being used substantially when facing procurement uncertainty. Risk and cost can be reduced by a flexible cooperation mechanism between buyer and supplier, such as a flexible sourcing contract and integrated decision making. Table V shows an overview of PRM modeling with integrated decision strategy.

Signing a flexible contract with supplier can also be used to reduce price risk. Li and Kouvelis (1999) tried to figure out the optimal purchasing time and quantity of “time-inflexible contract” and “time-flexible contract” individually. Time-inflexible contract requires buyer to determine not only the exact order quantity but also the purchasing time, while time-flexible contract allows buyer to purchase the specified quantity over a given period of time. In addition, risk sharing mechanism is also incorporated. The optimal result is obtained by calculating the net present value of the sum of purchasing cost and inventory cost. Actually Li and Kouvelis (1999) also proved that multiple sourcing is also beneficial for procurement under price uncertainty. Similar time-flexible contract is also used by other researchers to mitigate procurement risk (e.g. Fotopoulos et al., 2008; Xiong et al., 2011; Buzacott and Peng,
Option contract is another form of flexible contract. If the spot market price is lower than price specified in option contract, buyer could withdraw the right to execute option contract (e.g. Spinler and Huchzermeier, 2006; Fu et al., 2010).

Another effective way is the integrated production and procurement decision making. Chen et al. (2006) developed a two-stage decision model. The manufacturer determined the production quantity at the first stage when there is little information about the actual demand. In the second stage, as the selling season approaches, the buyer would place the order. At the last stage, a risk sharing contract was proposed to maximize the overall profit and each partner’s interest is also ensured. Burnetas and Gilbert (2001) made a tradeoff between more accurate demand information and the increasing price as selling season approaches. After modeling the uncertain demand using Bernoulli process and deriving the optimal solution, a numerical study is provided to give management insights on stocking policy with cost function. Mukhopadhyay and Ma (2009) studied a case when the used parts and new parts can be used as input for the production process. The yield of the used parts resulted in the demand uncertainty for new parts. Production and procurement plan are optimized simultaneously to reduce risks; the same approach is also used by Xu (2010). In addition, the procurement decision would also affect the inventory holding cost, integrated sourcing and inventory decision. Keskin et al. (2010) considered inventory replenishment, holding and backorder costs to meet stochastic demand. A simulation-optimization approach is adopted to obtain the procurement and inventory decision. One innovative approach of promoting cooperation between buyer and retailer is to use option contract. Zhao et al. (2010) suggested using the negotiating of option contract price and the exercise price instead of wholesale price mechanism to facilitate the production and procurement in the supply chain. To obtain the system-wide optimal expected profit for the supply chain, they took the whole supply chain as a centralized entity. The result is compared with the wholesale price mechanism in manufacturer-retailer cooperation and it is realized that the option contract can bring in Pareto improvement.

5.4 Hedging strategy

The hedging strategy is used to deal with uncertain price and demand. Financial hedging can be achieved by setting up a forward contract in one foreign currency such as US$ at the prevailing spot exchange rate to stabilize the earning and avoid volatility of company’s cash flow due to fluctuations of exchange rate. The operational hedging can be achieved by setting up a number of supply contracts or distributed manufacturing over the world

<table>
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<th>Reference</th>
<th>Demand</th>
<th>Price</th>
<th>Yield</th>
<th>Lead Time</th>
<th>Disruption</th>
<th>Correlation</th>
<th>Objective</th>
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</thead>
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<td>×</td>
<td>×</td>
<td>×</td>
<td>Maximize expected profit</td>
</tr>
<tr>
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<td>Fix</td>
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<td>×</td>
<td>×</td>
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<td>×</td>
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<tr>
<td>Zhao et al. (2010)</td>
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<td>×</td>
<td>×</td>
<td>×</td>
<td>Maximize profit</td>
</tr>
<tr>
<td>Inderfurth and Clemens (2014)</td>
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<td>Fixed</td>
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<td>Minimize the total procurement cost</td>
</tr>
<tr>
<td>Sajadieh and Thorstenson (2014)</td>
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<td>×</td>
<td>×</td>
<td>Random</td>
<td>×</td>
<td>×</td>
<td>Minimize the cost</td>
</tr>
</tbody>
</table>

Table V. An overview of procurement risk management models with integrated decision strategy
Various hedging strategy such as multi-stage hedging strategy, minimal-variance hedge and one-stage hedge are studied by scholars to deal with price volatility and demand uncertainty. Ni et al. (2012) adopted discrete-time control theory to resolve the problem of volatile procurement cost of material by adjusting the futures position at different stage. Harrison and Van Mieghem (1999) argued about the optimal of capacity imbalance can never be obtained until the demand is known but applying multi-dimensional newsvendor model allows firms to plan the capacity of critical resource so as to achieve near-optimal hedging. Real time pricing hedge contract types are studied in the work of Zhang and Ma (2009) through analyzing the demand pattern, contract price and hedged load percentage so as to find out the minimize the expected cost and penalty risk measure of the cost for electricity procurement. Moreover, Aouam et al. (2010) used both financial and non-financial contracts as gas procurement source, such as futures, options and storage. The naïve strategy is to hedge a fixed fraction of winter demand and equally allocated among available procurement sources. As hedging is commonly used in commodity market, Oum et al. (2006) has exploited the co-relation between load and price and adopted the hedging strategy by setting a portfolio of forward contract and call and put option.

For recent study, hedging strategy can also be used to tackle uncertain yield. Luo and Chen (2017) considered the effect of option contracts in hedging risk from a single period two-level supply chain with uncertain supply yield and deterministic market demand. The authors discover option contract can coordinate the quantity between order and production. As a result, an optimal supply chain performance can be achieved. Table VI shows an overview of PRM modeling with hedging strategy. Demand is generally regarded it as random variables while Yield is regarded as variable and random. Price is set as random and variable and some of studies concerns the correlation between yield and price. However, until now not many research considers about the lead time in the hedging strategy.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Demand</th>
<th>Price</th>
<th>Yield</th>
<th>Lead Time</th>
<th>Disruption</th>
<th>Correlation</th>
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</thead>
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<td>×</td>
<td>×</td>
<td>×</td>
<td>Maximize expected, discounted global, after tax value</td>
</tr>
<tr>
<td>Harrison and Van Mieghem (1999)</td>
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<td>×</td>
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<td>Variable</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Yield and price</td>
</tr>
<tr>
<td>Zhang and Ma (2009)</td>
<td>Random</td>
<td>Random</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Yield and price</td>
</tr>
<tr>
<td>Oum et al. (2006)</td>
<td>Variable</td>
<td>Variable</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Load and price</td>
</tr>
<tr>
<td>Giri (2011)</td>
<td>Fixed</td>
<td>Variable</td>
<td>Random</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Minimize expected profit</td>
</tr>
<tr>
<td>Silbermayr and Minner (2016)</td>
<td>Fixed</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Yes</td>
<td>×</td>
<td>Minimize total procurement cost</td>
</tr>
<tr>
<td>Luo and Chen (2017)</td>
<td>Fixed</td>
<td>Random</td>
<td>Random</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>Yield and price</td>
</tr>
</tbody>
</table>

Table VI. An overview of procurement risk management models with hedging strategy
low price lasts for a certain period before it returns to the normal price level. Chaouch (2007) considered such a problem and tried to design the optimal replenishment plan by using stochastic model. The optimal strategy is to replenish the products when the inventory falls below a certain level. It is the promotion period rather than the common policy that they should place the order when inventory level is zero or even when the price is high. Inventory management is seen as a risky investment for future by Tapiero (2008). By using exponential utility function and two-period model, he proved that zero-inventory can be replicated by option contract with the optimal order quantity. Facing uncertain raw material price, Arnold et al. (2009) also took the uncertain holding cost and uncertain demand into consideration by adopting a deterministic optimal control approach to design the procurement plan. The optimal policy turned out to be impulse or just-in-time procurement.

Actually the yield uncertainty can be reduced through supplier development program such as capital investment on improving the production line or quality inspection center. Therefore, the question is how much resources should be invested. Lin and Hou (2005) developed a model to reduce the yield variability through proper capital investment and to search the optimal ordering policies. Numerical studies found that the capital investment brought about an average savings of 13.6 percent cost. Talluri et al. (2010) also advocated that manufacturing firms should also allocate resources to improve suppliers’ capabilities and performance, including quality management, product management and cost reduction. The originality of Talluri's (2010) paper is to use Markowitz’s model to assist buyer and manufacturing firms in allocating supplier development investment among multiple suppliers optimally. The other contribution is to present an analytical approach to address the issue of risk in the capital investment for supplier development.

5.6 Implication of the study
Based on the findings of the study, it is realized that backup sourcing are frequently used to handle the disruption risk, uncertain lead time and uncertain demand. Multiple sourcing or dual sourcing inventory models are adopted by considering the market with dynamic cost, suppliers’ responsiveness, inventory availability. Schmitt and Tomlin (2012) consider and construct a graph of the effect on the performance among each strategy under disruption frequency, they conclude that supplier diversification is less often preferred than backup sourcing strategy as fixed supplier cost increase. Zhang and Liu (2011) also pointed out that although supplier diversification can reduce the dependency on the supplier, high procurement cost of this strategy is a vital problem for the company. After the comparison, backup sourcing is more benefit to the current company. Qi (2013) proposed to include waiting time in the continuous review inventory problem under random disruption. It comes to the managerial decision whether they should wait for the primary supplier recover form disruption with lower cost or get the supply from the backup supplier to reduce the market loss. Flexible contract is a commonly approach for dealing with the uncertain price and lead time. Among the research methodologies, stochastic and dynamic programming are mainly used for modeling the uncertainties. As not all parameters are deterministic and it is difficult to formulate the mathematical model in certain situation, discrete event simulation is another prefer alternative option to minimize the supply at risk by considering the demand distribution such as Poisson demand and yield mean of the selected suppliers.

6. Conclusions
In this paper, various uncertainties in procurement are examined. Especially, the uncertain demand, price, yield, lead time, disruption risks and multi-uncertainties are thoroughly investigated. After reviewing the published papers in the procurement risk domain,
research problems are summarized and classified. This work also provides a review of the latest strategies to deal with uncertainties.

It cannot be denied that there is gap between theory and practice. Referring to the studies of Sodhi et al. (2012), the gap may be narrowed down by conducting the case study on major procurement risk event before the empirical studies on PRM. Close collaboration with industrial partner may help to minimize the gap. The willingness to provide open data through the consortium platform may enable the theoretical framework to be more realistic. Having reviewed over 100 papers, authors come up the following concluding remarks and future research directions.

6.1 Multi-item procurement under uncertainty
Because of the complexities of this kind of problem, there are very few papers about purchasing multi-item by considering the risks (Dolgui and Ould-Louly, 2002). In reality, a product is usually made of several components, so the majority of buyer has to purchase several components at the same time. Under this multi-item situation, it is difficult to solve procurement decision under uncertainty as the corresponding stochastic models are too complex to obtain optimal solutions. Therefore, it is better to transform the models to deterministic models with the following methods such as the branch and bound algorithm, goal programming and simplex method. Moreover, the uncertainties within each item are correlated. Therefore, the future work should also consider the correlations among the various uncertainties (Fu et al., 2010; Xu, 2010; Zhang, 2010; Oum et al., 2006).

6.2 Risk taking awareness
The most popular way to treat uncertainty is to calculate the expected value of the objective function, while the variance of the outcome is also essential and should not be neglected. Some of the decision models obtain the best expected value but may be not the optimal value (Harrison and Van Mieghem, 1999). The optimal decision is the one with the best aggregate performance of both expected value and variance. The Value at Risk (VAR), which measures the biggest loss over a given period within a fixed confidence level, is a useful method to represent the variance (Gan et al., 2005). The benefit of VAR is that it could be used with the conventional statistical method together. Another useful method is the Conditional Value at Risk (CVAR), which is derived by a weighted average between value at risk and losses outside value at risk. The incorporation of VAR and CVAR could help decision makers to get a more detailed and useful result about the outcome (Tomlin, 2006).

6.3 Risk dependency
Currently, many models assume that uncertainties are independent, especially when the number of risk factors is more than two. But the risks are indeed correlated with each other (Oum et al., 2006, Sting and Huchzermeier, 2010). Traditionally multivariate normal distribution is used to model the dependence between uncertain factors. However, the incorporation of dependence into decision-making models usually makes it too complex to be solved, and another limitation is that the marginal distribution belongs to the same family. Copula function is used as a way to formulate a multivariate distribution in such a way that the general types of dependence can be represented. Copula may be a useful mathematical tool for further research (Wagner et al., 2009).

6.4 Lead time uncertainty
The accurate estimation of procurement lead time and on time delivery is a prerequisite of efficient production. It is often the case that buyers select those suppliers with the lowest cost but do not pay much attention to the lead time uncertainty. When the delivery cannot
meet the deadline, suppliers could not deliver all the products or even a portion of them. This shortage would cause manufacturing disruption, resulting in revenue loss. It is necessary to consider lead time uncertainty when selecting suppliers and making order allocation decisions (Hariga and Ben-Daya, 1999; Hsu et al., 2009; Wang and Tomlin, 2009). Besides, more research work can be done to explore the correlation about geographical location of suppliers and lead time or study the possibility of conducting certain inventory management strategy through reducing lead time uncertainty.

6.5 Yield uncertainty
Yield uncertainty can be due to the limited supplier capability or the defective items. Although many papers incorporate random yield in their models, the assumption is simplistic by assuming binomial yield uncertainty without considering how defective products are produced and affected by machine lifecycle. In addition linear cost is assumed in the recourse action and it is not always true in real situation (Yano and Lee, 1995). When considering yield uncertainty, the assumption should be more general and assumed to be stochastic. Indeed yield can be further studied if buyer and supplier can develop a cooperative relationship, for example, a flexible quantity contract is a proper way to promote sustainable development for PRM.

6.6 Reactive PRM
The majority of the papers try to reduce risks before the risk happens. A lot of mathematical models are proposed to consider many risks during the procurement decisions-making process (Haksöz and Kadam, 2009). However, in reality, good contingency plans may be more important than theoretical model for industrial practitioners. For instance, when supplier could not deliver on time, buyer could buy from spot market or place instant order. This may be expensive but the cost is usually smaller comparing with the cost of delay. Reactive risk management should be considered at the initial step for procurement decision making.

6.7 PRM using financial instruments
The development of financial instruments brings a lot of opportunities for procurement to better handle various kinds of risks, such as demand, yield, price and lead time. Multinational companies make use of financial hedging together with operational hedging to reduce the foreign exchange risk exposure (Kim et al., 2006). Foreign exchange swaps and financial derivatives help companies to mitigate the risk of loss. In addition, the application of Markowitz’s portfolio theory can be used to allocate resources for supplier development. Therefore, more research work should be conducted to expand the application of financial instruments for PRM.

References


Further reading


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