Integrated Operational and Financial Approaches

in

Supply Chain Risk Management

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Abstract

Integrated Operational and Financial Approaches in Supply Chain Risk Management

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Like other relatively more established sub-areas of Supply Chain Management, Supply Chain Risk Management (SCRM) is an emerging field that mostly lacks integrative approaches across disciplines. This study attempts to narrow this gap by developing an integrated approach to SCRM using operational tools and financial instruments. The conceptualization of SCRM is examined with reference to the broader literature on risk management. A SCRM framework is developed based on our taxonomies of risk and risk management approaches.

Our unit of analysis is a supply chain composed of an aluminum can supplier, a brewery and a distributor. We develop a (base) stochastic optimization model that incorporates operational and financial features of the aforementioned supply chain. The supply chain is exposed to aluminum price fluctuation and demand uncertainty. Through simulation based optimization, we compare the performance of the integrated model (under which operational and financial hedging decisions are made simultaneously) to a sequential model (under which the financial decisions are made after the operational decisions are finalized, a common practice for many supply chains even today). Using experimental designs and statistical analyses, we analyze the performance of the two models in minimizing the expected total opportunity cost of the supply chain. We examine the supply chain performance in different business environments defined by three factors, each at three levels: risk aversion, demand variability and aluminum price volatility. We find that the integrated model outperforms the sequential model in most cases. The results also shed light on significant variations in supply chain performance under changing business environments. Managerial insights are offered based on optimization results and statistical analyses.

The base model developed is then extended in two directions. First, we incorporate lead time variability as a fourth factor and study the effects of this variability. For the second extension, we introduce exchange rate risk into our base model. We examine the variations in the benefits of hedging exchange rate risk under two risk aversion levels and different exchange rate volatilities. Managerial insights on the findings of both extensions are provided.

The thesis concludes with a summary of overall findings. Areas for further research are also highlighted.

Dedication

To my lovely wife, Gisele, for all your support and hard work

To my wonderful kids, Fadi, Ghadi and Thea, for all the weekends and evenings this thesis kept me away from you

To my dear parents, Costy and Cathy, for all your sacrifices

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Contribution of Authors

This thesis consists of five manuscripts presented in order in Chapters 2 – 6. I am the first author in all these five manuscripts. The manuscripts are co-authored with my two co-supervisors, Dr. Ahmet Satir and Dr. Latha Shanker. The first two manuscripts (Chapters 2 & 3) are also co-authored with Dr. Yasemin Kahyaoglu. The first two manuscripts are accepted for publication in the journal *Risk Management*. The third manuscript (Chapter 4) is submitted for publication to the *European Journal of Operational Research*. The fifth manuscript (Chapter 5) is submitted for publication to the *Journal of Applied Finance*.

In the third manuscript, I am responsible for developing the model, running the simulation-based optimizations, performing the analyses of results and drawing managerial insights. Dr. Satir and Dr. Shanker supported me in the model development and provided guidance in the analyses and interpretation of results. In the fourth and fifth manuscripts (Chapters 5 and 6), I modified the formulation of the base model to incorporate the new factors.

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Chapter 1

Introduction

Supply chain risk management (SCRM) entails assessment of risks that may cause disruptions along a supply chain, and the implementation of tools that can be employed to manage these risks. Risk management has been widely studied in various disciplines from finance to engineering. However, supply chain risk management is a relatively recent undertaking. Supported by advanced information technologies and faster and cheaper transportation, firms are expanding their supply networks. Supply chains are geographically scattered all around the world. This worldwide presence substantially increases the exposure of the supply chain to inherent risks. The very structure of a supply chain results in exceptional far-reaching, global exposure. Such an exposure amplifies its vulnerability to traditional risks. Furthermore, the common business practices implemented in supply chains aggravate the impact of risks. For example, the just-in-time approach that characterizes the supply systems in most supply chains makes them vulnerable to stockouts, traditionally managed by inventory buffers. On the other hand, both the structure and the infrastructure of a supply chain can also positively contribute to its capability to manage risks. In this regard, the global presence of a supply chain increases its production flexibility and the partnership-like relationships among members of the supply chain make it more resilient to sudden changes in market conditions.

Identifying the imminent risks is the first step towards establishing a risk management strategy. Despite the significance of this task, the literature on SCRM is short on methods that help practitioners identify risks in a systematic manner. Once risks are identified, appropriate risk management tools are to be deployed. Literature in various disciplines is abundant with risk management methods. However, there isn't much research reported on how to select 'appropriate' risk management tools. To fill this gap in the literature, we develop a supply chain risk management framework, presented in Chapter 2, that supports the tasks of risk identification and selection of the appropriate risk management tool.

The purpose of our research is two-fold. First, we conduct a survey on supply chain risk management. The survey is based on an extensive review of the literature. In the first part of the review, we focus on risk identification and risk management in supply chains. We use our supply chain risk management framework in the second part of the review to classify the risks and risk management approaches found in the literature into categories. Based on these classifications, we associate risks with respective risk management tools. Second, we explore the benefits of integrating operational and financial approaches in mitigating risks in a supply chain. There is a profusion of risk management models in the operations and finance literatures. However, only a small number of studies reported investigate the advantages of integrating the two approaches. Moreover, few risk management models optimize the performance of the supply chain as a unit. Most of such models are buyer centric. We contribute to the SCRM literature by developing a model that integrates operational decisions (via procurement and inventory levels) and financial hedging decisions (via financial derivatives) in order to minimize the opportunity cost of the supply chain as a whole.

In Chapter 2, we review the literature on the main stream research of risk management and we elicit elements that are specific to risk management in supply chains. In the main stream of risk management, we identify two gaps in the literature pertinent to risk identification methods and systematic procedures to select the appropriate risk management approach. We attempt to fill this gap by developing a supply chain risk management framework. The principal components of the framework are the classification methods of risks and risk management approaches. Based on our literature review, we propose to identify risks through three different constructs: risk domain, source of risk and adverse events. We also propose to classify risk management approaches into three categories: avoidance, prevention and mitigation approaches. Such a classification facilitates the risk management selection decision. Finally, we develop a planning process that facilitates the implementation of our framework in the context of a supply chain risk management strategy.

In Chapter 3, we present the findings of our literature survey on risk management approaches. The survey is based on an extensive review of the operations and finance literatures. The operational risk management approaches are reviewed in line with our supply chain risk management framework. In each of the four risk domains, defined in the framework, we associate various adverse events identified in the literature with sources of risks. Then, we discuss how different operational approaches reviewed can be deployed for avoiding, preventing or mitigating these risks. We also assign these approaches to functional areas. Our review for the finance literature focuses on the financial derivatives that are commonly used in risk management to manage the operating cash flow of manufacturing firms. From our review of both literatures, we note the differences between operational and financial approaches in risk management. We also observe the presence of conflicting arguments. Some researchers contend that operational and financial approaches are substitutes, while others argue that they are complements. We complete our literature survey with a review on integrated operational and financial approaches. We recognize gaps in this relatively sparce literature.

Motivated by the scarcity of research on integrating operational and financial tools to manage risks in supply chains, we develop a model to explore the benefits of integrating these two approaches. In Chapter 4, we present our base model in which our unit of analysis is a supply chain consisting of a brewery, a can supplier and a distribution center. The supply chain encounters two uncertainties: fluctuation in aluminum prices and variability in beer demand. The former affects the cost of an important input to the production process, which is the cost of aluminum cans. The latter leads to a mismatch between the output quantity and the realized demand. Before the demand is realized, the supply chain needs to make two decisions: i) quantity of aluminum to procure, and ii) inventory level to maintain in the distribution center. Associated with the first decision is an opportunity cost should the aluminum price decrease. The opportunity cost pertinent to the second decision stems from the stockout costs and the holding costs. The latter cost is also a function of the aluminum procurement price in the first decision. The supply chain hedges the aluminum price with inventory and options on aluminum futures and coordinates the flow of empty cans and beer across the supply chain. The above decisions are made with an objective of minimizing the expected total opportunity cost along the supply chain.

We formulate this stochastic problem in our base integrated model and find the solution using a simulation-based optimization algorithm. We use experimental design to study the effects of three factors on supply chain performance. These factors are risk aversion level, demand variability and aluminum price volatility. We create various treatments representing all possible permutations of these factors. Each factor is represented at three levels. We also compare the results of the integrated model with corresponding results of a sequential model. This latter model captures the situation in which the supply chain first makes decision on inventory levels and then makes decisions on financial hedging. Comparing the corresponding expected total opportunity costs of the two models sheds light on the benefits of integrating operational and financial tools in supply chain risk management. The findings reveal that, in most of the cases, the supply chain can better manage its risks when it integrates the operational and financial risk management approaches. However, under certain business conditions, integrating the decisions would not lead to significant improvements. We also find that the supply chain uses less operational hedging in the integrated model. More operational hedging is used when demand variability increases and when the supply chain is more risk averse. Our statistical analyses for the optimal solutions obtained in the various treatments substantiate the impact of each factor and explains the interaction effects among the three factors on the expected opportunity cost.

In Chapter 5, we present an extension to our base model. In this extension, we incorporate a stochastic lead time in the supply of aluminum cans to the brewery. While in the base model this lead time is assumed to be deterministic with a fixed duration of four weeks, it follows a discrete probability distribution with a mean of four weeks in this extended model. Similar to the experiments in the base model, we create a number of treatments representing all possible permutations of the factors. In addition to the three factors studied in the base model, lead time variability constitutes the fourth factor. Each factor is represented at two levels. We implement the same solution method (simulation-based optimization) used in the base model. For analysis, we focus on the effects of lead time variability on the performances of the integrated and the sequential model. We also interpret the interaction effects involving lead time variability on the expected opportunity cost. Lead time variability is found to significantly alter the effects of the risk aversion level on the expected opportunity cost and the effects of demand variability on this cost.

In Chapter 6, we examine the performance of an international supply chain in which the brewery and distribution center operate in Canada and the can supplier operates in the United States. In addition to the aluminum price volatility and demand variability which are considered in the base model, the supply chain is exposed to fluctuation in the CAD/USD exchange rate. We incorporate this new risk factor in an extension to the base model. We simulate various sets of exchange rate with different volatilities to better investigate the effects of this risk on the supply chain performance. We incorporate these volatilities in different treatments of the integrated model. We solve these treatments at two levels of the risk aversion factor, keeping the other two factors constant at their base levels. We perform parametric analyses on the optimal results and we present some managerial insights. While the positive effects of hedging the exchange rate are predictable, the results reveal the influence of the risk aversion level and the exchange rate volatility on these effects.

In the final chapter, we summarize the findings of the literature survey for the pertinent articles. We underline the major findings in the base model and the two model extensions. We highlight the major managerial insights elicited from the results of the three models. We conclude by proposing some directions for future research in SCRM

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Chapter 2

Supply Chain Risk Management – I: Conceptualization, Framework and Planning Process

2.1 Introduction

While research on risk management is extensive and crosses over various academic disciplines at the firm level, it is imperative that risk management also be studied within a supply chain context in which the unit of analysis is the supply chain rather than the firm. Though the nature of risk does not change, the exposure profile of a supply chain to such risks is different from that of a single firm. On the one hand, the structure and practices of supply chains make the participating firms more vulnerable to the traditional risks encountered by single firms. The widely used just-in-time (JIT) inventory system is a typical example of a supply chain practice that exposes firms to material shortage risk. On the other hand, the structural characteristics of supply chains also allow firms to join forces to minimize such risks. For example, information sharing among members of the supply chain is known to reduce the bullwhip effect.

Supply Chain Risk Management (SCRM) entails managing risks that can hinder the performance of supply chains. SCRM is a developing area of research as indicated in, among others, Juttner *et al* (2003), Juttner (2005), Tang (2006a), Khan and Burnes (2007), and Manuj and Mentzer (2008b). This Chapter contributes to this research through the development of a SCRM framework and an accompanying risk management planning process that help the user set a comprehensive risk management strategy. The framework is based on a typology involving three constructs of risk. These constructs are 'risk domain', 'source of risk' and 'identified risk'. Risk management approaches are classified in the framework as 'avoidance', 'prevention' and 'mitigation' approaches. The developed framework associates various risk management methods found in the literature with identified risks.

Manuj and Mentzer (2008a) define global SCRM as "the identification and evaluation of risks and consequent losses in the global supply chain, and implementation of appropriate strategies through a coordinated approach among supply chain members". Three major elements can be elicited from this definition of SCRM: risk identification and evaluation/assessment, global supply chain and coordinated risk management strategies. We structure our work in the next three sections around these elements. In Section 2.2, we review papers on risk identification and assessment. Because of scant coverage of risk identification and assessment methods in the literature, we underscore the role of proper risk classification in identifying risks and we emphasize the evaluation of risk dimensions as an assessment requirement. In Section 2.3, we accentuate the particular relationship between risks and global supply chains. Particularly, we highlight the vulnerability of these supply chains to risks, as well as their ability to alleviate risks.

In Section 2.4, we argue that the various risks in supply chains should be managed by the coordinated and collaborative efforts of the stakeholders involved. Despite the abundance of methods that can be used to manage risks, we highlight the lack of selection criteria in the literature when implementing these approaches. Based on the conceptualization and review in the preceding sections, we then present our SCRM framework in Section 2.5 and the risk management planning process in Section 2.6. Our contribution to the literature is summarized in Section 2.7.

2.2 Risk Identification and Assessment

While the main objective of supply chain risk management is well articulated in terms of protecting the supply chain from any risk that can adversely affect its performance and continuity, the problem often lies in the difficulty in identifying the risks in the first place. Once risks are identified, supply chain practitioners face the subsequent challenge of assessing these risks in order to develop the appropriate risk management strategy. In the following sub-sections, we underline the lack of identification methods in the literature and review the assessment methods described by researchers.

2.2.1 Risk Identification

The first step in the risk management process is the identification of the risks posing threats to the supply chain. Kleindorfer and Saad (2005) and Svensson (2001) emphasize the necessity of identifying risks as well as their sources to enhance risk management. However, the literature suffers from a shortage of risk identification methods (Rao and Goldsby, 2009). Acknowledging this shortage, Neiger *et al* (2009) propose a methodology based on value-focused process engineering (VFPE). The perception of risk as a process objective allows the authors to use the VFPE (a methodology usually used to identify objectives) in identifying supply chain risks.

2.2.1.1 Risk Classification

Risk classification is regarded as a prerequisite in identifying risks. Miller (1992) argues that his classification of the uncertainties encountered by international firms would clarify the "relevant dimensions" of these uncertainties. The author presents three major categories of uncertainties: general environment, industry and firm. Under each category, a number of major classes of uncertainties are identified. Specific factors are then listed under each class, encompassing the different dimensions of uncertainties. Triantis (2000) classifies risks into five major categories. These are the technological, economic, financial, performance and legal/regulatory risks. The financial category comprises four sub-categories, of which one is the foreign currency exchange rate risk. The author then discusses three distinct risks stemming from exchange rate risk: transaction, translation and competitive risks. The identification of these three risks illustrates the direct benefits of effective risk classification as the distinctions among the identified risks are useful in assigning the proper risk management approach. In their 1994 survey, Bodnar *et al* (1995) find that 80% of the firms which use derivatives hedge their commitments (transaction risks), 44% of the firms hedge the balance sheet (translation risks), and 40% hedge economic exposure (competitive risks). Risk classification is also essential for assessing the risks (Juttner *et al,* 2003). This argument is supported by Sheffi and Rice (2005) who identify three classes of possible disruptions to the firm: random events, accidents and intentional disruptions. They contend that the method of estimating the likelihood of each class differs. Consequently, risk classification is thus indispensable for setting the appropriate risk management strategies. Chopra and Sodhi (2004) call for managers to "understand the universe of risk categories as well as the events and conditions that drive them" to be able to develop effective supply chain risk management tools. In this context, one can refer to various categories defined by a number of researchers in their attempts to classify risks and sources of risks (e.g. Ghoshal, 1987; Miller, 1992; Ritchie and Marshall, 1993; Triantis, 2000; Svensson, 2001; Juttner *et al,* 2003; Christopher and Peck, 2004; Chopra and Sodhi, 2004; Tang, 2006a; Ritchie and Brindley, 2007; Manuj and Mentzer, 2008a; Blos *et al,* 2009). In Section 5.1, we discuss our risk classification as part of our supply chain risk management framework and we compare our typology with some of the existing classifications.

2.2.1.2 Risk Identification Factors

Although risk classification facilitates a systematic identification of potential risks, identification of risk is argued to be a function of two factors: managers' perceptions and characteristics of the industry (Miller, 1992; Juttner *et al,* 2003). Managers' perceptions of risks may be influenced by personal factors such as emotions, gender, age and education level (Moen and Rundmo, 2006; Cohen and Kunreuther, 2007). The results of a survey carried out by Moen and Rundmo (2006) reveal that worry is the main predictor of the public's perception of transport risk. The manager's personal factors may be more objective such as his/her own evaluation of market movements (Servaes *et al*, 2009). Contending that such managers' perceptions are "static or are seldom updated", Blackhurst *et al* (2005) call for developing broader and dynamic risk models. On the other hand, with respect to industry characteristics, Sheffi and Rice (2005) argue that the exposure of different firms to a certain risk is distinctive. For example, while bad weather is a major source of risk for Disney's theme parks (Meulbrock, 2002), it is of small significance for a traditional manufacturing company. From their exploratory interviews with supply chain practitioners, Juttner *et al* (2003) find out that these managers conceptualize risk based on the specific supply chain they manage and the industry where they operate.

2.2.2 Risk Assessment

2.2.2.1 Risk Assessment Methods

Once various risks are identified, managers then proceed to assess risk to evaluate its potential impact on the firm's performance. Despite the lack of research concerning the process specific to supply chain risk assessment (Zsidisin *et al,* 2004), a number of researchers have a common understanding that risk assessment entails the evaluation of two variables: i) likelihood of occurrence of an adverse event and ii) magnitude of the impact on the supply chain's performance should the event occur (e.g. Cox and Townsend, 1998; Chopra and Sodhi, 2004; Sheffi and Rice, 2005; Cohen and Kunreuther, 2007; Knemeyer *et al,* 2009; Thun and Hoeing, 2011). In the failure mode and effect analysis (FMEA) methodology, risk assessment entails a third variable, detection of failure, that needs also to be estimated (Stamatis, 2003). Due to the macro nature of supply chain risks (delayed shipments, change in demand, earthquake, etc.) we assume that adverse events are visible and thus we omit the failure detection variable from our discussions. The likelihood of occurrence and the magnitude of impact are largely agreed to be the basic dimensions of risks in the supply chain literature. March and Shapira (1987) define risk as "the variation in the distribution of possible supply chain outcomes, their likelihood and their subjective values." The "outcome" in this definition clearly refers to the realization of risk in the form of an adverse event. The same term was used earlier by Moore (1983) who describes the two main components of risk to be the ‘future outcome’ and the occurrence likelihood of this outcome. Ritchie and Brindley (2007) elicit from the various definitions of risk a third dimension which is “the causal pathway leading to the event” (see also Kleindorfer and Saad, 2005). A similarity can be noted between this third risk dimension and one of the questions formulated by Sheffi and Rice (2005) for vulnerability assessment: “What can go wrong?” While occurrence probability and impact magnitude provide a two-dimensional construct defining a risk, this third dimension leads to another attribute of risk management: source of risk or risk driver. In Section 5.1, we recognize the source of risk as a major construct of our framework and we emphasize the benefits of explicitly highlighting the sources of risk when developing an effective supply chain risk management strategy.

2.2.2.2 Risk Measurement

In a supply chain context, risk assessment also involves locating parts of the chain that are most susceptible to risk and portraying the form of damage that may be endured in case the adverse event occurs (Cohen and Kunreuther, 2007; Knemeyer *et al,* 2009). At this stage, managers face the challenging task of quantifying the likelihood of occurrence of the adverse event and the magnitude of its impact on supply chain performance. While the likelihood of occurrence can be measured using historical data, the impact level can be measured in financial terms (e.g. loss in returns, value at risk), operational terms (e.g. production delay period, number of customers not served) or in strategic terms (e.g. loss of goodwill, loss of market share). The severity of impact may also be in itself a factor in determining the proper mitigation tool to use. Huang *et al* (2009) develop a model to distinguish between ‘deviational’ and ‘disruptive’ risks. While the impact of the former is limited to variations in system parameters and outcomes, the latter would disrupt normal operations and result in unpredictable system performance. One challenge is to find the appropriate information to quantify the risk measures (Knemeyer *et al,* 2009). Haimes (1998) proposes the use of frequency data, scenarios and subjective probabilities or experts’ judgments. Sheffi and Rice (2005) contend that historical data may be used to measure the occurrence probabilities of ‘random events’ and ‘accidents’. However, the authors acknowledge that this task is more challenging in the case of ‘intentional disruptions.’ An example of the use of expert judgment to quantify the two risk dimensions is the empirical study done by Thun and Hoenig (2011). The authors surveyed supply chain managers and logistics managers in the German automotive industry to estimate the probability of occurrence and the consequences of a number of risks on a five-point Likert scale ranging from very low to very high. Measuring the occurrence likelihood and the adverse consequences are essential elements in quantifying risk, that Kleindorfer and Saad (2005) expect any “disciplined” risk assessment process would generate. The conversion of the two risk dimensions into a measure for the corresponding risk is formulated by Brindley (2004) as the product of the probability of a risk incident and its business impact. On the financial side, Huchzermeier and Cohen (1996) measure the downside risk of exchange rate variations as the expected deviation of a firm's discounted value from a specified level. In a more complex method, the exchange rate risk exposure is initially estimated using the standard two-factor market model (Jorion, 1990). Then, a multivariate regression model estimates the exposure as a function of operational and financial hedging positions (Allayannis *et al,* 2001; Kim *et al,* 2006). Canbolat *et al* (2007) estimate the dollar values of various sourcing risks based on their occurrence probabilities and impacts. The authors use these risk values in a simulation model that enables the user to perform a complete assessment for potential failures and, accordingly, identify an appropriate risk mitigation strategy.

2.3 Risks in Supply Chains

While risk management is extensively studied in the context of single firms, risk management in supply chains is a growing stream of research for two main reasons. First, interdependencies of firms through their traditional supply and demand transactions make the focal firm vulnerable when another firm on its upstream or downstream side encounters adverse events. This interdependence motivates studies of supply chain risks (Cohen and Kunreuther, 2007). Furthermore, the characteristics and practices of supply chains alter the nature of exposure of chain members to traditional risks, facilitating the emergence of new approaches to manage these risks.

In the context of SCRM, we focus on two main characteristics of supply chains: structure and operational practices. The structure of a supply chain is typified by the global presence of the members of the chain and by the integrated business processes among these members. Some of the operational practices that are pertinent to risk management are the lean production system, single sourcing and information sharing across the supply chain. These practices can easily be contrasted to their conventional counterparts of mass production, multiple sourcing and unit-based information flow. To make our discussion more tractable, we elaborate more on the above two characteristics and on their implications for risk management.

2.3.1 Supply Chain Vulnerabilities

The competitive advantages of a supply chain are made possible by the effective exploitation of its network design and the efficiency of its operational processes. Coupled with these benefits, however, are the threats to the supply chain that make it more vulnerable as its risk exposure is altered by its structure and practices.

2.3.1.1 Supply Chain Structure

Globalization, although a major attribute of a supply chain structure, is not an exclusive characteristic of supply chains. While many companies have overseas suppliers and market their products in foreign countries, other supply chains operate purely on a domestic level. However, operating globally exposes supply chains to a number of pertinent risks (Manuj and Mentzer, 2008a). In fact, the empirical results of Thun and Hoenig (2011) show that globalization is the most prominent supply chain risk driver perceived by the respondents of their study. Risks in supply chains stem from various sources including socio-political and economic developments, natural and man-made disasters and fast changes in market requirements (Tang, 2006a; Khan and Burnes, 2007). The worldwide location of production facilities and the flow of products across countries expose firms to uncertainties in exchange rates and input prices (Ding *et al,* 2007). Globalization is also found to be a statistically significant driver for catastrophic risks. In their large-scale empirical study, Wagner and Bode (2006) found that global sourcing makes supply chains vulnerable to catastrophic risks such as terrorist acts, socio-political crises, natural disasters and epidemics.

The complexity of a supply chain structure plays a significant role in its vulnerability (Harland *et al,* 2003; Tang, 2006b; Neiger *et al,* 2009). Lambert *et al* (1998) identify three aspects of the complex structure: members, structural dimensions and types of process links. The 'focal' firm, from whose perspective the network is designed, integrates its 'value-adding' processes with the 'primary' members and receives support from 'supporting' members. The number of tiers across the chain and the number of firms within each tier determine the 'horizontal' and the 'vertical' structure respectively. While these two structural dimensions reveal the breadth and depth of the whole structure, the 'horizontal position' is a dimension that locates a specific company along the width of the structure. Finally, the authors identify four types of business process links based on the extent of involvement of the focal firm. These links can be managed, monitored, non-managed or non-member process links. This classification facilitates the allocation of the appropriate resources to manage these business processes in an efficient manner. The links between firms in the supply chain structure are not independent business-to-business relationships, but collectively make the supply chain a "network of multiple businesses and relationships" (Lambert and Cooper, 2000). As competition between discrete firms is changing to competition between supply chains (Christopher, 1992), a robust supply chain structure provides members of the chain a competitive edge. However, the complexity of the supply chain structure also gives rise to new sources of risks that are "network-related", namely uncertainties due to three factors: chaos, lack of ownership and inertia (Juttner *et al,* 2003). An example of 'chaos' is the well-known 'bullwhip effect' (Lee *et al,* 1997) that depicts increasing fluctuations of order quantities from the downstream to the upstream of the supply chain. In general, the lack of confidence among members of the supply chain leads to such chaos and increases the vulnerability of the supply chain (Christopher and Lee, 2004). The lack of ownership stems from the complex relationships that a firm may develop with its upstream and downstream partners. These relationships can be so complicated that the responsibilities of the various members in delivering the end product become uncertain. Inertia risks are associated with lack of responsiveness to changes in the business environment and market conditions.

2.3.1.2 Supply Chain Practices

The vulnerability of supply chains due to globalization and network complexity, as discussed above, can be classified as 'structural' as it is directly related to the physical and tangible configuration of the supply chain. Accordingly, one can categorize the vulnerabilities caused by the procedural and intangible configuration of the supply chain as 'infrastructural'. The vulnerability to catastrophic events illustrates the distinction between these two categories. Knemeyer *et al* (2009) notes that not only the physical global spread of supply chains expose them to more natural or man-made catastrophes, but also the lower 'slack' in inventory diminishes the opportunities to deal with these events. Hence, one can intuitively conclude that the structural vulnerability of supply chains involves increases in the likelihood of adverse events, while the infrastructural vulnerability involves the ability to mitigate the consequences of these events.

Blackhurst *et al* (2005) and Svensson (2002) relate the vulnerability of supply chains to an increase in the use of supply chain practices, such as increasing responsiveness to customers, achieving higher agility and operating lean systems. Many authors relate the adoption of lean management practices to the increase in the supply chain vulnerability (e.g. Norrman and Janson, 2004; Thun and Hoenig, 2011). Such practices encompass, among others, just-in-time (JIT) arrival of material at any production workstation when needed. The implementation of JIT creates time and functional dependencies within the supply chain, rendering it vulnerable to potential disruptions (Svensson, 2002), due to the fact that any adverse event occurring at any node of the chain will affect the other nodes (Norrman and Janson, 2004). Single sourcing is another practice widely used in supply chains. Despite various benefits of single sourcing such as ease of management, quantity discounts from order consolidation, reduced order lead times and logistical cost reductions (Burke *et al,* 2007), purchasers are obviously affected by any problem encountered by their sole supplier (Kelle and Miller, 2001).

2.3.2 Supply Chain Characteristics Contributing Positively to Risk Management

In previous sections, we argued that various characteristics of supply chains make them more vulnerable to risks. However, one can contend that the characteristics of supply chains also enable firms to better implement some risk management strategies and even create new opportunities to manage risks. There is a direct relationship between the geographical dispersion of supply chains and their risk exposure. It is evident that the global activities of a supply chain expose the participating firms to various risks that emanate from this global environment. However, this global presence can provide a firm the ability to overcome risks originating from exchange rate fluctuations. Hommel (2003) argues that a firm's global presence creates two risk management opportunities: operational flexibility and geographic diversification. The former provides the real option of switching production between facilities in two countries to offset any adverse change in the exchange rate between the two currencies. The latter can perfectly substitute for a symmetric financial hedge, normally used by exporters, by locating a production facility in the foreign country to manage exchange rate risk. One other aspect of supply chain structure is the tight integration among its members. Braunscheidel and Suresh (2009) report that the external integration of a firm with key suppliers and customers is the strongest driver of the 'firm's supply chain agility'.

‘Structural’ risk management capabilities of supply chains are complemented with ‘infrastructural’ capabilities acquired by the supply chain practices. Information sharing is one such capability that integrates the supply chain. Information sharing can significantly reduce the possibility of a ‘bullwhip’ effect by efficiently exchanging the actual demand data from the point-of-sales to the multiple upstream suppliers. Eliminating distorted information makes the supply chain better prepared to respond to changing market needs (Masson *et al,* 2007). Information sharing also reduces uncertainties through more accurate demand forecasting (Guo *et al,* 2006), inventory levels, sales promotion strategies and marketing strategies (Mentzer *et al,* 2001).

2.4 Supply Chain Risk Management

The challenge that confronts the stakeholders along the supply chain is to develop an effective and comprehensive risk management strategy that i) exploits the partnership-like relationships among the members, ii) attempts to manage all the risks concurrently and iii) employs the most suitable risk management approach for each type of risk (Cohen and Kunreuther, 2007).

2.4.1 Collaborative Risk Management

Risk management should be regarded as a key business process that draws the contributions of the different firms of the supply chain as well as the input from their respective divisions. Relationships in a supply chain are different from a sequence of traditional buyer-seller relationships. Cooper and Ellram (1993) contrast these two types of relationships by using eleven characteristics. In supply chains, the firms work closely to manage the chain as one entity having a channel-wide inventory, cost evaluation, planning and risk sharing. Cooper *et al* (1997) elaborates this perspective for supply chains by depicting the major business processes infiltrating across the members of the chain and through the functional divisions of each firm. In a survey conducted by Servaes *et al* (2009), 63% of the participating companies acknowledge the benefits of a firm-wide approach to risk management. Previous studies had concluded that managing risk on a firm level is more effective than on a functional level (Miller, 1992). Companies may even incur losses when individual functional divisions attempt to implement risk management approaches in isolation from other departments. Proctor & Gamble and Metallgesellschaft suffered catastrophic losses after they took positions in financial derivatives that were not consistent with their corporate strategy (Froot *et al,* 1994). Triantis (2000) explains the rationale for sharing risk by highlighting two main capabilities of a firm which is willing to assume the risk. Such a firm will either have the capability to bear the risk or the capability to better control and manage this risk. The decision of which risks to bear and which risks to transfer to others is a central responsibility of corporate risk management.

2.4.2 Concurrent Risk Management

Risk management along a supply chain can never be regarded as a set of independent approaches aimed at mitigating discrete risks. There are mainly three reasons for this. First, risks in supply chains are so interconnected that one risk gives rise to other risks or influences the outcome of another (Manuj and Mentzer, 2008a). Exchange rate risk directly impacts the demand for products produced in one country and sold in another. Fluctuations in the currency exchange rate would change the demand for a manufacturer's product by foreign customers because of their diminished purchase power. Second, mitigating one risk can aggravate the exposure to another risk (Miller, 1992; Chopra and Sodhi, 2004). For example, keeping inventory buffers to mitigate demand uncertainty increases the exposure to inventory obsolescence. Third, actions taken by one member of the supply chain to mitigate a risk which threatens his firm's performance may create risks for other members (Chopra and Sodhi, 2004). Vendor managed inventory is a typical example in this regard under which inventory related risks are passed onto a supplier (or a third party). For all these reasons, the selection of risk management approaches should bear minimum contradiction (Braunscheidel and Suresh, 2009). The principal objective should be to minimize the exposure of the supply chain, as a whole, to all types of risks.

2.4.3 Selection of Risk Management Approaches

The literature in the various disciplines, such as operations management, marketing, finance and strategy, are rich with numerous approaches that can be employed in risk management. Nevertheless, Khan and Burnes (2007) underscore a shortcoming of this abundance. The authors note that a strategy which is used to reduce a specific risk may also become a source of another risk. For example, single sourcing is adopted by firms to exploit the exceptional relationship that they develop with their single supplier. While this strategy can minimize poor quality and lead time risks, the buyer is highly exposed to the risk of disruption in the supplier's business. The effectiveness of a risk mitigation tool can also vary with the extent to which this tool is implemented. Swink and Zsidisin (2006) study the effects of a focused commitment strategy (FCS) to suppliers on five dimensions of manufacturers' competitive performance: cost efficiency, quality, delivery, profitability and market share growth. As a result of their survey, the authors conclude that, except for 'quality', FCS has positive effects on four of the dimensions studied up to a certain implementation level beyond which these benefits can be offset by risks. Implementation of some mitigation tools may increase the complexity of supply chain systems and consequently aggravate their risk exposure (Yang and Yang, 2010). These authors evaluate the effects of mitigation tools on the system's complexity in terms of two factors: tight coupling and interactive complexity. They refute a common belief that a postponement strategy aggravates supply risk, arguing that postponement, though characterized by tight coupling, can decrease interactive complexity and thus protect firms from supply disruptions.

The method deployed to manage risk may depend on the firm's specific circumstances. Considering an information gathering process as a means to reduce risk by buyers, Mitchell (1995) relates the nature of such a process to the level of expertise of the buyer, the level of risk and the company's size. The selection of a risk management approach depends also on implementation costs. Firms should ensure that the cost does not exceed the benefits of eliminating or reducing the risk (Miller, 1992; Chopra and Meindl, 2003; Servaes *et al,* 2009).

The literature is short on providing guidelines for selecting suitable supply chain risk management approaches (Manuj and Mentzer, 2008a). This deficiency makes it difficult to come up with a general process to set a comprehensive risk management strategy. Froot *et al* (1994) observed that “there is no single, well-accepted set of principles” that guide the hedging programs of the various firms. Many researchers, nonetheless, provide a classification of the various risk management approaches which compensates for the absence of systematic guidelines to select a risk management approach that best fits a specific supply chain environment (e.g. Miller, 1992; Svensson, 2001; Juttner *et al,* 2003; Chopra and Sodhi, 2004; Sheffi and Rice, 2005; Tang, 2006a; Thun and Hoenig, 2011). Our work attempts to narrow this gap by developing a comprehensive taxonomy that classifies the various approaches used in risk management and the large number of discrete risk events listed in the literature. In the risk management paradigm developed by Kallman and Maric (2004), the authors describe the process of selecting the risk management tool to be a brain-storming activity. To facilitate such a selection activity, our taxonomy associates each approach with a well identified risk originating from a risk domain. In the following section, we present the supply chain risk management framework developed using our taxonomy. We also compare our taxonomy to the extant categories in the literature.

2.5 A Framework for Supply Chain Risk Management

The supply chain risk management (SCRM) framework developed is presented in Figure 2.1. The framework encapsulates various types of risks listed in the literature, as well as the diverse approaches used to manage these risks. A specific adverse event is associated with a source of risk and a source of risk is linked to a risk domain. The framework facilitates the classification of risk management approaches based on risk management objectives. Functional areas in the focal firm and supply chain stakeholders responsible for the implementation of the risk management approach are also incorporated in the framework. In the following sub-sections, we present the underlying constructs of our risk and SCRM approach taxonomies. We will clarify the distinctions among the three risk management approaches used, followed by a discussion on the distinction between source of risk and identified risk.

2.5.1 Risk Taxonomy

To classify risk events, we identify three distinct constructs for our taxonomy: i) domain of risk, ii) source of risk and iii) adverse event.

i) Domain of risk: We identify four domains in which the source of risk exists. ‘Internal Operations’ is the domain that includes all the factors associated with performing the core process adopted by a firm in converting inputs into the desired output. ‘External Stakeholders’ is the domain related to the operations of the suppliers, outsourced companies, distributors and any other party who is involved in supplying materials / components and / or services. The third domain, ‘Marketplace’, includes all the market-related factors pertinent to the specific industry in which the firm operates.

Lastly, ‘Environment’ is the domain covering all the non-market related factors, such as government regulations and natural disasters. A comparison of our four risk domains and other classifications reported in the literature is presented in Table 2.1.

Table 2.1 Comparison of risk domains used in the SCRM literature

Our Risk Domains	**Rao and Goldsby (2009), adapted from Ritchie and Marshall (1993)**	**Juttner et al. (2003)**	**Miller (1992)**	**Christopher and Peck (2004)**
Internal Operations	Organizational risk	Organizational risk sources	Firm uncertainties	Internal to the firm
External Stakeholders	Industry risk	Network-related risk sources	Industry uncertainties	External to the firm but internal to the supply chain network
Marketplace				
Environment	Environmental risk	Environmental risk sources	General environmental uncertainties	External to the network

Identifying the domain for each source of risk is an important step in the risk management planning process. It is usually easier for a firm to reduce the occurrence likelihood of an event when its source originates from ‘Internal Operations’ rather than from ‘Environment’. On the other hand, avoiding a risk originating from ‘Marketplace’ may prove to be more difficult than avoiding a risk stemming from ‘Internal Operations’. Thun and Hoenig (2011) report statistical significance for the difference between their ‘internal’ and ‘external’ supply chain risks in terms of occurrence likelihood and their impact.

ii) Source of risk: This construct identifies source groupings for major risks within each risk domain. For example, for the risk domain ‘Marketplace’, the sources of major risks can be identified as: demand uncertainty, currency exchange rate fluctuation and marketplace randomness.

iii) Adverse event: Different events can emanate from the same source of risk. A separate analysis should be performed for each one of these events as the corresponding risk management approaches can be different. For example, an unreliable supplier is a source of shipment delays as well as quality problems.

The distinction between the source of risk and the adverse event is crucial for the risk analysis process. While supplier unreliability is considered as one of the risks encountered by buyers, we recognize it as a source of different adverse events, such as poor quality, price fluctuations and delays in supply. The risk management approaches to deal with these three distinct events can vary substantially. In a similar vein, the identification of three distinct types of currency fluctuation risks in finance (transaction, translation and competitive/economic risks) enables firms to establish effective risk management strategies (Triantis, 2000). The approach used to manage transaction risk is completely different, in various aspects, from that used to manage competitive risk. Kim *et al* (2006) find from the results of their empirical study that firms exposed to currency exchange rate fluctuations effectively use currency derivatives to manage transaction risks and use operational geographic dispersion to manage competitive risks.

2.5.2 Taxonomy for Risk Management Approaches

To classify the various risk management approaches presented in the literature, we identify three distinct constructs:

i) Avoidance approaches: These are methods that significantly reduce or eliminate the company's exposure to specific sources of risk. For example, Disney theme parks are located in warm areas to avoid the negative impact of cold weather.

ii) Prevention approaches: These are methods that reduce the occurrence probability of an adverse event that may emanate from an existing source. For example, firms may use multiple suppliers for a given component to reduce the likelihood of one supplier's failure to supply the right quantity and quality at the right time.

iii) Mitigation approaches: These are the methods used to reduce (if possible, eliminate) the negative impact of the adverse events. For example, a flexible product strategy via postponement helps the firm minimize the impact of a change in demand in the product mix.

The connection between risk management approaches and the definition of risk is evident in two of the risk dimensions. The 'occurrence likelihood' is decreased by the 'prevention approaches' and the 'impact level' is reduced by the 'mitigation approaches'. There is also a connection between the 'avoidance approaches' and the third dimension of risk as argued by Ritchie and Brindley (2007). This third dimension is the 'causal pathway' described as "the nature of the event and the sources and causes that generate it". This connection is depicted in our SCRM framework in Figure 2.1 by the arrows originating from a 'risk domain' and reaching an 'adverse event' via a 'source of risk'.

A comparison of the above three categories of risk management approaches and similar typologies developed by other authors is presented in Table 2.2.

Table 2.2 Comparison of classifications for risk management approaches used in the literature

<table>
<tr><th>Our Classification</th><th>Juttner et al. (2003), adapted from Miller (1992)</th><th>Thun and Hoenig (2009)</th><th>Servaes et al (2009)</th></tr>
<tr><td>Avoidance approaches</td><td>Avoidance</td><td rowspan="3">Preventive instruments</td><td>Hedging</td></tr>
<tr><td rowspan="2">Prevention approaches</td><td>Control</td><td rowspan="2">Diversification</td></tr>
<tr><td>Co-operation</td></tr>
<tr><td>Mitigation approaches</td><td>Flexibility</td><td>Reactive instruments</td><td>Insurance</td></tr>
</table>

2.6 Supply Chain Risk Management Planning Process

In line with the framework presented in Figure 2.1, we propose the use of a risk management planning process (given in Figure 2.2) to set a comprehensive risk management strategy, potentially incorporating operational, financial and marketing elements. While the framework provides the building blocks of this strategy, the planning process navigates the user through a logical sequence of reasoning required to put these blocks together to come up with a comprehensive risk management strategy. The planning process organizes possible events and corresponding approaches in a chronological order that helps the user make a simulation-like risk analysis. This chronology applies for both the risk management approaches and the stages of risk. Figure 2.2 depicts each of the three risk management approaches in a specific position within the planning process that is in line with the implementation timing of the corresponding approach. Similarly, the different stages of risk are depicted in an increasing order of realization. While the upper half of the process chart depicts risk as an imminent threat, the lower half presents the advanced risk stages: occurrence of an adverse event, its consequences and mitigation actions taken once the outcomes have been evaluated. The upper and lower halves of the planning process are also different in terms of scope. While the upper half is pertinent to various risks identified by the focal firm, the lower half entails the management of the identified risk by the focal firm in close collaboration with various supply chain members. When all risks identified are assessed and measured, the firm can then prioritize risks in terms of the occurrence probability and impact level. The planning process then leads the user through the subsequent decisions and actions that may very well involve other stakeholders. Based on its risk evaluation, the firm makes one of three possible risk management decisions: i) retain the risk, ii) transfer the risk or iii) share the risk with a partner / member of the supply chain. Whereas in the first option, the firm does not incur any cost a priori but would bear all the consequences should the adverse event occur, the second option shields the firm from adverse consequences for a pre-determined cost. The third option involves a compromise under which both the protection cost and the consequences are shared in a predetermined manner by the parties involved. The constructs of risk and risk management approaches, discussed in Sections 5.1 and 5.2, respectively are shown in Figure 2.2 as an oval shape to distinguish these from the decision (diamond shape) and action (rectangular shape) constructs.

The illustrative example in Figure 2.3 shows how the planning process is deployed to set an 'operations based' risk management strategy that protects a firm from supplier's unreliability. Emanating from the external stakeholders domain, the unreliability of a supplier that provides critical components is a source of risk that can result in a number of adverse events, namely poor quality, shipment delays and price hikes. One starts with evaluating the degree of exposure to such a source of risk. A firm with few suppliers for critical components is more exposed than a company with many suppliers. The former firm can significantly reduce its exposure by building a network of suppliers and implementing a stringent supplier selection process. These two strategies are identified as avoidance approaches due to their impact in terms of significant reduction in risk exposure. However, such approaches may not be applicable in the case of highly customized components which can only be produced by one or two suppliers. For the risk identified in terms of shipment delays, the firm can adopt a prevention approach to reduce the likelihood of encountering delays by maintaining a closer relationship with the supplier, such as providing free technical support in production scheduling and / or in transportation. Should the delays continue to persist, the firm would then compare the estimated cost of the risk impact (such as, paying penalties to its own customers for late shipments of finished products) to the cost of implementing a mitigation approach (such as, holding higher levels of inventory). If the former cost outweighs the latter cost, the firm may decide to use higher inventory levels. As this lessens the impact of the supplier's shipment delays, such an action is considered as a mitigation approach. The risk management strategy may need to be re-evaluated following the implementation of each avoidance, prevention and / or mitigation approach, as indicated in the last box in Figure 2.2. This re-evaluation is especially more pronounced following the implementation of an avoidance approach, due to its likely long term impact on the firm's operations.

2.7 Contribution to the Literature and Concluding Remarks

The taxonomy (Table 2.1 – 2.2), framework (Figure 2.1) and planning process (Figure 2.2) contribute to the literature on supply chain risk management in a number of ways. The taxonomy helps the user to make a goal-based classification of the risk management approaches. We identify three distinctive goals in this respect, namely: i) to eliminate or significantly reduce the company's exposure to the source of risk, ii) to reduce the likelihood of occurrence of an adverse event and iii) to reduce the impact of such an occurrence. We refer to the risk management methods deployed to achieve these three goals as ‘avoidance approaches’, ‘prevention approaches’ and ‘mitigation approaches’, respectively.

Such a taxonomy helps the user to distinguish between the source of risk and the manifestation of that risk. For example, while some of the reviewed articles list ‘supplier unreliability’ as a risk, we interpret it as a source of risk which can be manifested in the different forms of longer lead time, poor quality and increased supply cost. This distinction is essential for the proper selection of the risk management approach to be deployed.

The framework encompasses the assignment of risk management approaches to functional areas in the focal firm and / or to external stakeholders that are responsible for the implementation of these approaches. The inclusion of this assignment link in our framework stems from our vision of supply chain risk management as a business process that needs to be integrated within the functional areas of a firm and across the members of the supply chain. The same argument was promoted by various authors, such as Juttner (2005) and Seshadri and Subrahmanyam (2005), among others. This need for integration will be further elaborated on in Chapter 3. Lambert *et al* (1998) list a number of business processes that are integrated across the supply chain to become ’supply chain business processes’. The authors argue that such an integration requires coordination among the various departments within a company and among various companies along a supply chain. Through our work, we contribute to the list of Lambert *et al* (1998) a new set of processes: supply chain risk management approaches of avoidance, prevention and mitigation.

The framework and the planning process developed can also be used by supply chain managers to establish a comprehensive company-wide risk management strategy. The distinction among the three categories of risk management approaches helps practitioners to evaluate the various strategies available for implementation based on the corresponding payoff. Chapter 3 provides an extensive literature review of operational and financial approaches used for supply chain risk management based on the taxonomy and the framework reported in this chapter.

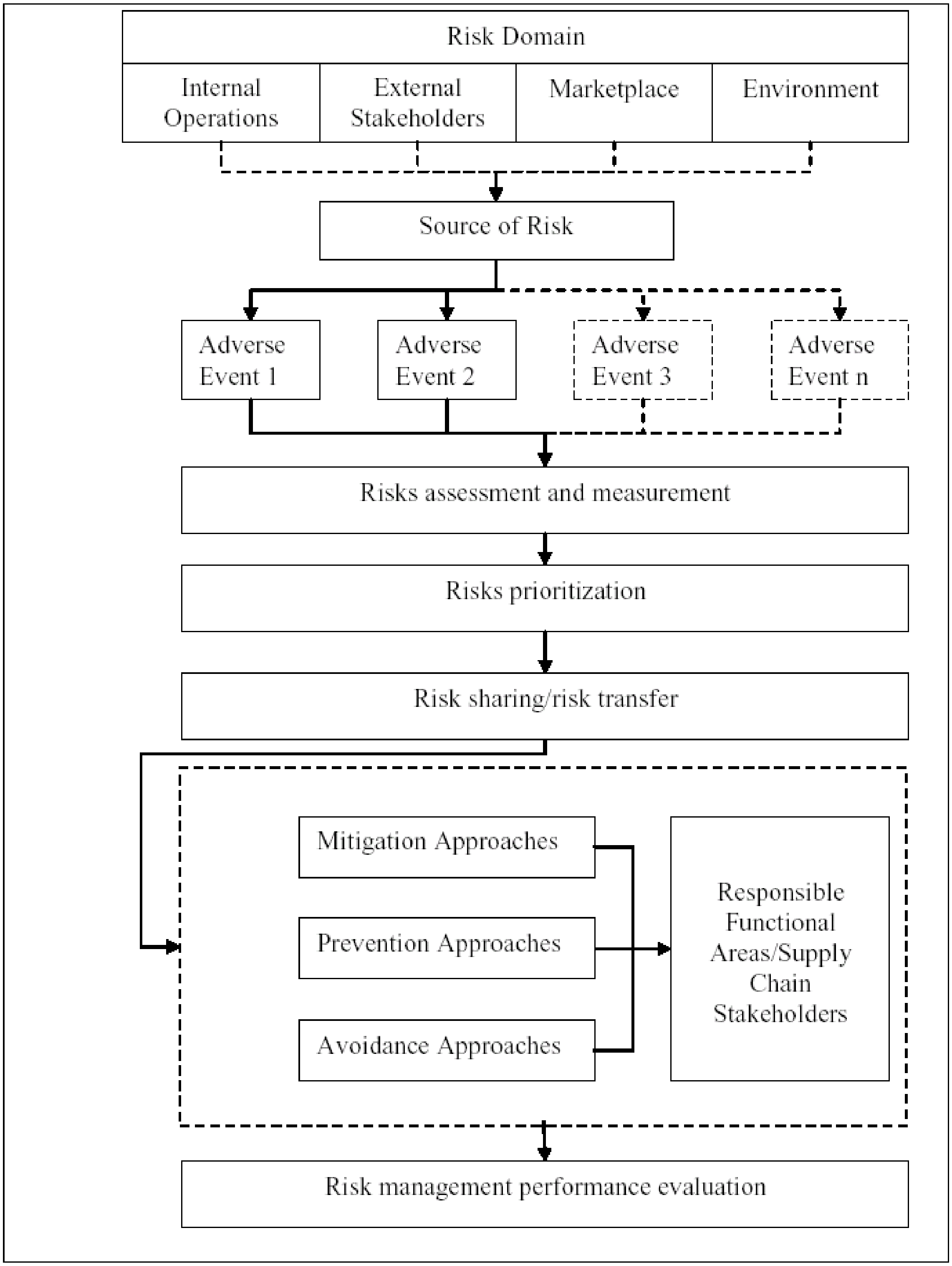

Figure 2.1 Supply chain risk management framework

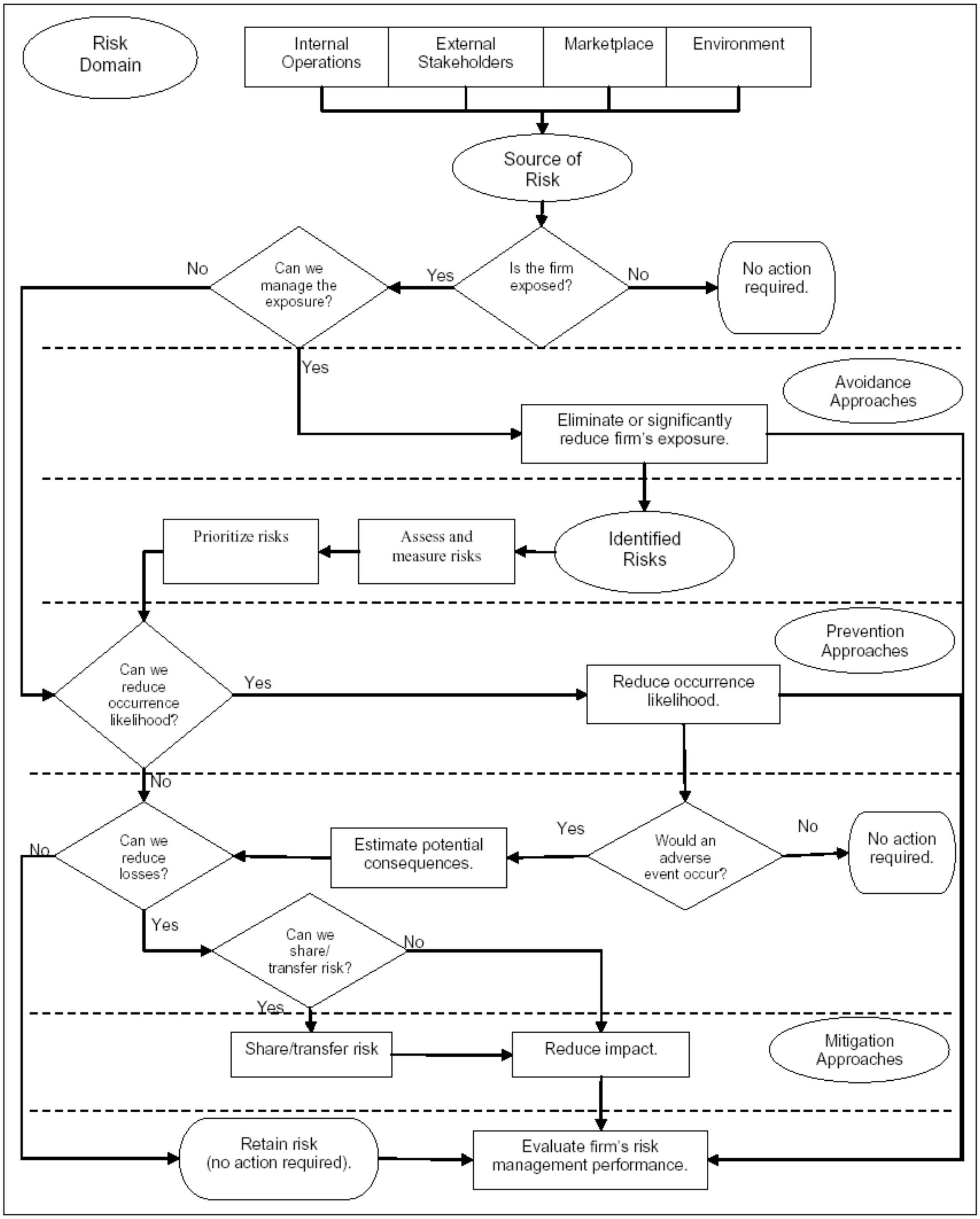

Figure 2.2 Risk management planning process

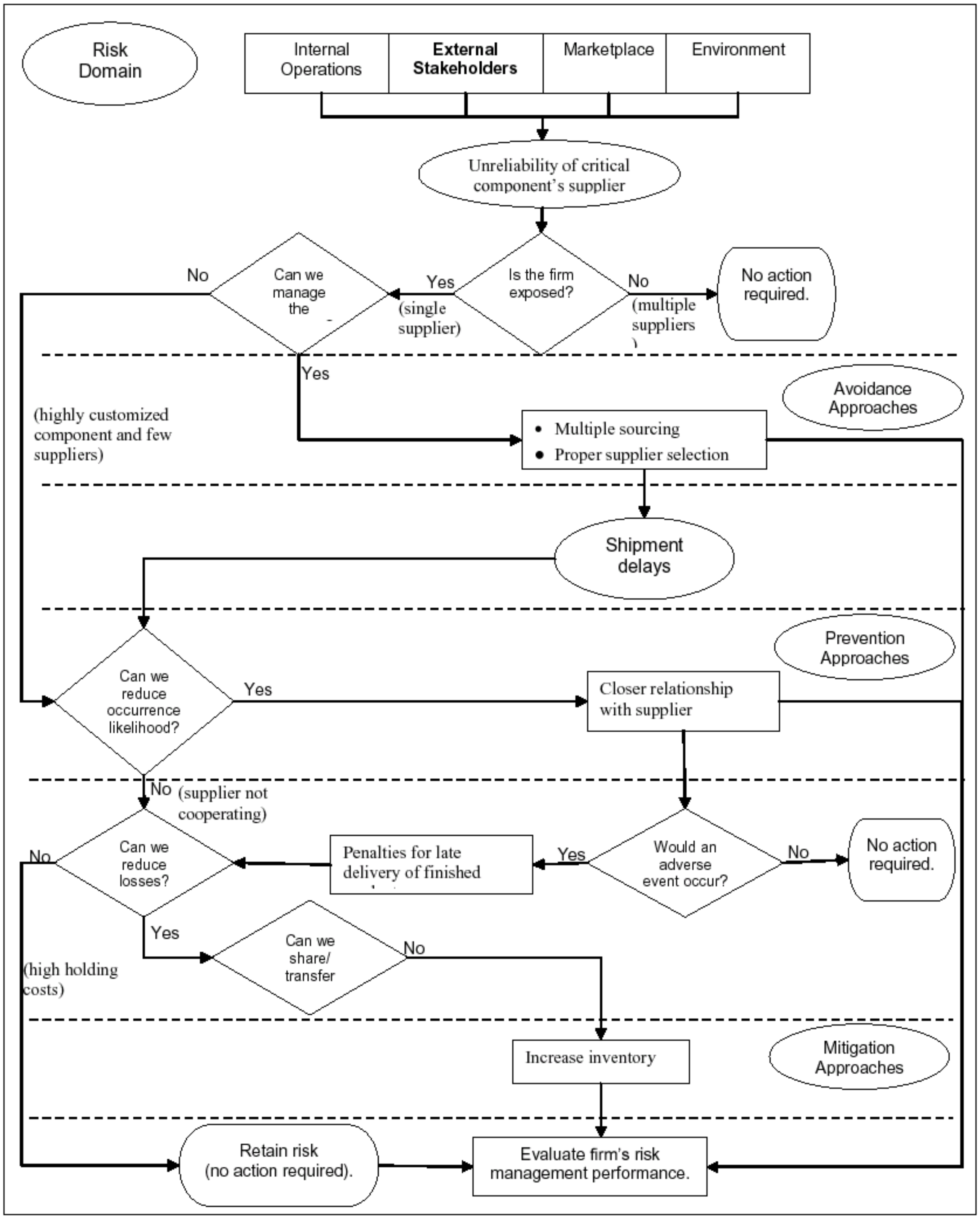

Figure 2.3 Illustrative example of risk management planning process

Chapter 3

Supply Chain Risk Management – II: A Review of Operational, Financial and Integrated Approaches

3.1 Introduction

This review classifies and analyses operational, financial and integrated approaches used when dealing with supply chain risks. The review is structured around the supply chain risk management (SCRM) framework and typology presented in Chapter 2. The framework identifies four risk domains: internal operations, external stakeholders, marketplace and environment. The typology classifies risk management methods into avoidance, prevention and mitigation approaches. The primary focus of the review is on multinational manufacturing companies, although the risk management approaches of non-manufacturing firms, such as service providers, retailers and distributors, are also addressed.

Section 3.2 reviews 'operational' risk management approaches with a focus on interaction between the firm and its supply chain partners. Section 3.3 reviews 'financial' risk management approaches, where the focus is on the use of financial derivatives. The section examines the key pertinent issues in integrating these instruments with operational approaches. Section 3.4 highlights the distinctions between operational and financial approaches. ‘Integrated’ operational and financial approaches are reviewed in Section 3.5. Section 3.6 presents major gaps in research in the extant literature and proposes areas for future research.

3.2 Operational Risk Management Approaches

3.2.1 Internal Operations

For the risk domain ‘internal operations’, three sources of risk are identified: process uncertainty, information system failures and labor uncertainty. The literature on operational approaches used when managing these risks is reviewed in the following sub-sections. A summary is provided in Table 3.1.

3.2.1.1 Avoidance Approaches

Cucchiella and Gastaldi (2006) address risks such as insufficient production capacity or delays in receiving critical information and examine ‘real options’ risk avoidance strategies such as, deferring investment, outsourcing, scaling down and abandoning current operations.

3.2.1.2 Prevention Approaches

Turnbull (2007) suggests adoption of quality control processes with supportive information systems to detect defective products before shipment to the end user to protect against the risk of product contamination. Use of ‘P-Trans-net’ model is proposed in Blackhurst and O’Grady (2004) to identify those nodes along the supply chain that contribute to the longest lead times and delays. Using ‘real options’ as prevention strategies are argued in Cucchiella and Gastaldi (2006). These include: i) ‘stage’ option, which provides the ability to abandon a project in midstream in light of new information unfavorable to continuing the project, ii) ‘lease option’ which provides the ability to lease an asset with an option to buy it at a later time, and iii) ‘growth option’ such as spending on research and development, leasing undeveloped land and strategic acquisitions, which could lead to future growth through access to new markets or strengthening core capabilities.

3.2.1.3 Mitigation Approaches

Sheffi and Rice (2005) argue that ‘conversion flexibility’, which involves the use of standard processes across facilities with built-in interoperability, allows a firm to operate in another facility when one is disrupted or to replace sick or otherwise unavailable operators. According to Tang and Tomlin (2008) and Thun and Hoenig (2011), a ‘flexible process strategy’ allows the firm to produce multiple products efficiently and to compete on product variety and cost.

3.2.2 External stakeholders

The sources of risk are identified for the risk domain ‘external stakeholders’ are: supplier reliability, distribution and network. The literature on operational approaches used when managing these risks are reviewed in the following sub-sections and summarized in Table 3.2.

3.2.2.1 Avoidance Approaches

The ‘real options’ cited by Cucchiella and Gastaldi (2006) and described in Section 3.2.1.1 could be used to avoid supplier quality and reliability issues.

3.2.2.2 Prevention approaches

Prevention methods can be classified into supply management and supply control approaches.

Supply management approaches address the impact of supplier reliability and demand uncertainty on the cost and lead time of different configurations of supplier networks. These include: i) management of supplier relationship, ii) supplier selection process, iii) use of supplier certification programs and iv) allocation of orders among suppliers. Tang (2006a) identifies four types of 'supplier relationships' in terms of: vendor, preferred supplier, exclusive supplier and partner. Each may be differentiated on the basis of contract type, contract length, information exchange, pricing scheme and delivery schedule. Sheffi and Rice (2005) and Tang (2006a) contend that corporate strategy should be aligned with the type of supplier relationship. The latter study addresses the use of various models for the final supplier selection, which incorporate the supplier's quality and the buyer's quality control policies, as well as the buyer's flexibility to shift the order quantity among suppliers dynamically in response to fluctuating exchange rates, when sourcing occurs in a multinational context. Various studies are classified in the area of allocation of orders among different suppliers while accounting for risks such as demand uncertainty, uncertainty in supply yields, supply lead times and supply costs. 'Supplier certification programs' to reduce supply-side quality and delivery reliability problems are suggested as a prevention approach in Thun and Hoenig (2011). Wu and Olson (2010) use stochastic DEA VaR (value-at-risk) approach and a stochastic dominance model to conduct a vendor evaluation study using twelve criteria over four categories of quality, price, performance and facilities / capabilities. The findings indicate that both the model used and the risk level specified both affect the supplier ranking. However, both models used yield consistent rankings at extremes, for the most efficient and the worst performing vendors.

Supply control approaches may take the form of vertical integration (Klibi *et al* 2010), increased stockpiling, use of buffer inventory and excess capacity in production, storage, handling and / or transport or imposing contractual requirements on suppliers (Juttner *et al* 2003). With respect to disruptions in inbound or outbound shipments, Sheffi and Rice (2005) advocate building 'tracking and tracing capabilities' to detect disruptions and take corrective action across the supply chain. 'Disruption discovery' approaches, referred to in Blackhurst *et al* (2005), include 'predictive analysis' using technologies such as intelligent search agents (data/text mining) and 'dynamic risk index' tools, to search for disruption related information. Early warning signs of potential or increasing risks provided by such tools would be used to highlight these areas within the supply chain that warrant attention.

3.2.2.3 Mitigation Approaches

Among the mitigation approaches, 'flexibility' approaches are aimed at reducing supply cost risks. Juttner *et al* (2003) suggest 'localized sourcing' to reduce lead times and improve response times. Tang and Tomlin (2008) suggest the use of quantity flexibility contracts, to mitigate supply commitment risks or the inability to change the order quantity once submitted. Tang (2006b) suggests the use of 'time-based supply contracts' to deal with uncertain wholesale prices imposed by the manufacturer. In a 'time inflexible contract', the buyer must state the purchase time upfront. In a 'time flexible contract', the buyer may observe price movements and decide dynamically when to buy. 'Disruption recovery' strategies, reported in Blackhurst *et al* (2005), are about flexible, real time 'supply chain reconfiguration' tools, which will take effect once a disruption occurs. An example of such a tool is an adaptive agent or configurable distributed software component that continually realigns goals and processes. Agents are used for task performance, task decomposition and distribution, even resource allocation among the distributed tasks, coordination of mixed initiative supply chain planning, scheduling and partner selection.

'Redundancy' approaches such as the use of safety stocks or multiple sourcing are suggested by Thun and Hoenig (2011), who use a survey of the German automotive industry to conclude that redundancy strategies are effective (but inefficient) means to deal with supplier quality and unreliability issues. Tomlin (2006) offers possible risk mitigation strategies for 'supplier order allocation' for the case of two alternative suppliers, who differ on reliability, volume flexibility and unit price. This enables rerouting of supply in case the preferred supplier is down. The choice of supplier and the amount of inventory carried depends on the level of uptime.

In Canbolat *et al* (2007), a comprehensive set of local and global sourcing risk factors (identified by six departments of a car company) are quantified into metrics. Expert judgments are used to determine the magnitude and the impact of these risks. Then, a process failure mode effects analysis is conducted and simulated to rank causes of failures and failure modes, to calculate total risks in terms of dollars and to evaluate optimum risk mitigation strategies. Swink and Zsidisin (2006) hypothesize that, based on a survey of 224 manufacturing plant managers, the relationship between their focused commitment strategy to suppliers and buyer's manufacturing performance (measured over five dimensions of cost efficiency, quality, delivery, profitability and market share growth) is non-linear, taking the form of an inverted u-shaped curve, with the exception of ‘quality’ which exhibits a positive linear relation.

3.2.3 Marketplace

For the risk domain ‘marketplace’, three sources of risk are identified: demand uncertainty, uncertainty in foreign exchange rates and uncertainty in prices of raw material, labor, energy and finished products. The literature on operational approaches used when managing these risks are reviewed in the following sub-sections and summarized in Table 3.3.

3.2.3.1 Avoidance Approaches

Thun and Hoenig (2011) advocate focusing on products with constant demand and few variants, or focusing on secure markets to manage uncertainty in demand volume and demand mix. Such a ‘focused factory’, which focuses on a narrow product mix for a particular market niche would outperform a conventional plant with a broader mission, since its equipment, support systems, and procedures can concentrate on a limited task for one set of customers, thus generating lower costs and overheads than those of the conventional plant .

3.2.3.2 Prevention Approaches

Prevention approaches incorporate demand management and information management strategies.

Demand management strategies, as described by Tang (2006a), involve shifting demand across time, markets or products. This is to be achieved by offering advance purchase discounts such as those used in travel service reservations, offering price discounts to customers who accept late shipments, phasing out old products and introducing new products. Other examples include ‘product substitution’ which aims to reduce the variance of aggregate demand by offering products with surplus inventory as a substitute for out of stock products and ‘product bundling’ which is used by retailers to force customers to buy a number of products as a bundle, such as computer and printer, shampoo and conditioner, to shape effective demand.

Information management strategies as suggested in Tang (2006a) and Thun and Hoenig (2011) may take the form of quick response systems, use of RFID, tracking and tracing devices (used to respond to actual demand rather than demand forecasts) for fashion products with short life cycles. For functional products with longer life cycles, these approaches include sharing demand information with supply chain partners, vendor managed inventory and collaborative forecasting and replenishment planning strategies. Juttner *et al* (2003) suggest cooperation strategies among supply chain partners to share information on exposures to specific risk sources and prepare joint business continuity plans. Blackhurst *et al* (2005) suggest strategies to identify bottlenecks at different nodes of the supply chain. Short-term predictions relating to seasonality of demand, etc. can be used to exploit alternate routing, delaying/expediting product flows and/or inventory positioning. Swafford et. al. (2008) suggest the use of ERP to manage global supply chain activities to deal with supply/demand mismatch risk, shorten product life cycles and customize delivery, speed, mix and volume.

3.2.3.3 Mitigation Approaches

Mitigation approaches include postponement and flexibility strategies.

Postponement strategies are addressed in Juttner *et al* (2003), Yang *et al* (2004), Tang (2006a) and Tang and Tomlin (2008). ‘Product development’ postponement, which facilitates customization of the final product, is enabled by technologies such as virtual prototypes, web-based voice of the customer method, and automated and distributed service exchange systems. ‘Production postponement’, which is about downstream positioning of production activities to the distributor, retailer or end user, is useful in markets in which a single product may have multiple derivatives due to different language, culture, government or technological requirements, and greatly reduces inventory carrying and transportation costs. An example on the application of production postponement is the model developed by Cholette (2009). Options of labeling and packaging postponements by a winery to mitigate the variation risk of demands from distinct sales channels are incorporated into a two-stage stochastic linear model. The postponement value is quantified by comparing the expected profits between the scenarios with and without postponement. The profits in the former scenario are found to be higher by 18%. ‘Logistics postponement’ is conducted by frequent / smaller size shipments or use of a rolling warehouse to achieve savings in inventory which would otherwise have to be stocked at numerous locations and to achieve improved matching of demand and inventory. Yang and Yang (2010) conclude, through drawing insights emerging from the theoretical principles in ‘normal accident theory’, that postponement may offer superior advantages over other risk mitigation strategies employed for supply chain disruptions.

Flexibility strategies, discussed in Sheffi and Rice (2005) and Tang and Tomlin (2008), include ‘flexible pricing strategy via responsive pricing’, which is used to entice customers to products with more secure components to reduce demand risks. 'Flexible supply strategy via flexible supply contracts', as reported in Tang (2006a), aims to achieve channel coordination. 'Wholesale price contracts' take the form of order up to newsvendor solution which is extended with the flexibility of placing two separate orders before the start of the selling season, hence allowing for demand updating. 'Buyback contracts' are used to induce the retailer to order more when faced with demand uncertainty. For products that do not have any buyback value, such as video rentals, 'revenue sharing contracts' are used to provide an incentive to the retailer to stock more. 'Quantity based contracts' are used to entice retailers to commit their orders in advance to achieve operational efficiency under demand uncertainty. 'Backup agreements' are used in the fashion apparel industry to allow the retailer to place his orders in two consecutive stages, after observing a few weeks of sales data, and to offer the flexibility for changing the order at a penalty cost.

'Contractual flexibility' as a risk mitigation strategy is reported in reference to the market of specialty chemicals in Reimann and Schiltknecht (2009) as well as in reference to wafer manufacturing at Intel in Vaidyanathan *et al* (2005). In the former study, contractual flexibility is the capability of the manufacturer to select the product portfolio and the option of postponing delivery dates for that portion of final demand that is revealed on the due date to protect against cancellation risk / delivery failure penalties imposed by the customer. The selection of the product portfolio depends on the availability of 'operational flexibility' which is defined as the percentage of available capacity of volume, as well as changeover capabilities. In the latter study at Intel, 'contractual flexibility' refers to the capability of the manufacturer to change order specifications of the required lithography exposure tools from their suppliers to protect against the risk of supply/demand mismatches resulting from short product life cycles. Tang (2006a) suggests that 'flexible process sequencing' can be used to reduce forecast uncertainty by reversing the sequencing of manufacturing processes as exemplified by Benetton's knit-first-dye-later strategy. 'Operational flexibility', (referred to in Kogut and Kulatilaka (1994) and Huchzermeier and Cohen (1996), among others) denotes the capability of switching production among multiple countries to safeguard against exchange rate risk. Spinler and Huchzermeier (2006) use valuation of options on capacity as a measure against seller's cost, buyer's demand and market price uncertainties for storable goods or dated services. The authors show that options contracts offer risk sharing benefits for the buyer and the seller and superior capacity planning. In Mello *et al* (1995), 'flexibility in sourcing' is about switching sourcing among multiple countries, in response to sharp movements in exchange rates, thus reducing the need to hedge foreign currency denominated revenue. The level of flexibility and the debt structure determine the level of hedging required. 'Flexibility of production assets' focuses on safeguarding against price uncertainty in power markets (Doege *et al* 2009) and derives from the power supplier's entry into a long position in the virtual storage of some part of the production capacity over and above a short position in the constant supply of power.

In Swafford *et al* (2008), supply chain flexibility covers procurement, distribution, manufacturing and product development functions and represents abilities to reduce supply chain lead times, ensure production capacity and provide product variety to improve customer responsiveness. 'Supply chain network design' is proposed in Klibi *et al* (2010) as a risk mitigation strategy to protect against fluctuations in prices of finished products, raw material prices, energy costs, labor costs and exchange rates. In their two stage stochastic network design model with recourse anticipation structure, it is assumed that the design variables (such as the number, location and capacity of entities like suppliers, manufacturing plants, distribution and/or sales centers, demand zones and the means of transportation) are to be solved in the first stage. The outcome of the design variables is then observed and the network usage variables provide the recourses necessary to make sure that the design obtained is feasible. 'Resource flexibility' mechanisms, (such as, capacity buffers, production shifting, overtime and subcontracting, safety stock pooling and placement strategies, flexible sourcing contracts), and 'shortage response actions' (such as product substitution, lateral transfers, rerouting shipments or delaying shipments) are suggested as possible response policies. The authors argue that these policies can be reflected into the recourse anticipation structure of the network design model. They cite examples such as defining second stage flow variables between production and distribution centers, if lateral transfers are permitted, or adding recourse variables and constraints to reflect overtime policy, or defining flow variables from suppliers by considering dual sourcing. It is also argued that in order to take 'aversion to value variability' into account, risk measures such as mean-variance or conditional value at risk functions instead of the expected value criterion need to be incorporated into the models.

Kumar *et al* (2010) offer optimal operating policies for a global firm conducting business in various countries. A stochastic multi-objective mixed integer programming model is developed. The model attempts to minimize the costs associated with supplier side risks, manufacturer / distributer / retailer risks and demand side risks, as well as, the costs of operating the supply chain. An optimal policy is determined based on the initial information available. In the later stages, by considering changes in risks' expected values, a shift in the flow quantities within the supply chain is determined in order to minimize disruptions and consequently the total cost of operations.

3.2.4 Environment

The five sources of risk identified for the risk domain 'environment' are: natural disasters, major accidents, political / sociopolitical conditions, willful attacks and regulations. The literature on operational approaches used when managing these risks is reviewed in the following sub-sections. A summary is provided in Table 3.4.

3.2.4.1 Avoidance Approaches

Klibi *et al* (2010) address avoidance approaches for risks associated with product markets, suppliers or facility locations due to the instability of the associated geographical area. Possible strategies proposed are closing some network facilities, delaying an implementation, rejecting an opportunity or using outsourcing for high risk product markets. Cucchiella and Gastaldi (2006) cite 'real options' strategies to protect against risks associated with changes in taxation and local regulations.

3.2.4.2 Prevention Approaches

Prevention approaches include 'catastrophe models' which are used in the insurance industry to estimate the location, severity and frequency of potential future natural disasters, offering tradeoffs between economic loss and the probability that a certain level of loss will be exceeded on an annual basis. Klibi *et al* (2010) claim that 'supply chain network design' models that incorporate assessment of hazards have not been proposed yet, but qualitative approaches to identify and assess supply chain disruptions are available. A two stage 'supply network design' model to examine the effects of financing, taxation, regional trading zones and local content rules on the design of a global supply chain is developed by Tang (2006a). Sheffi and Rice (2005) state that there is a need for situational awareness and initiative at levels closest to the disruptive event. 'Empowering frontline employees' to take initiative and act quickly on the basis of available information would contribute to the resilience of the supply chain.

3.2.4.3 Mitigation Approaches

These include flexibility and redundancy approaches.

Klibi et. al (2010) suggest incorporating flexibility approaches such as 'resource flexibility mechanism' and 'shortage response actions' into the supply chain network design as possible risk mitigation strategies, as explained in detail in Section 3.2.3.3. 'Resilience strategies' would necessitate investing in supply chain network structures before they are needed. The authors provide examples of design decisions such as selecting production / warehousing systems that can support several product types and real time changes, choosing suppliers that are partially interchangeable and locating distribution centers to ensure that all customers can be supplied by a backup center with a reasonable service level if the primary supplier fails. On the other hand, redundancy approaches, which involve duplication of network resources in order to continue serving customers while rebuilding after a disruption, are costly to implement according to Klibi *et al* (2010). 'Insurance capacity' is about maintaining production systems in excess of normal requirements, whereas 'insurance inventory' refers to a buffer position kept for critical situations.

A 'business continuity plan' is about instantaneous development of alternate suppliers to ensure uninterrupted flow of work. Page (2008) reports that Cisco's business continuity plan spared its global network from disruption after an earthquake hit China's Sichuan province, home to a major Cisco supplier. Ratick *et al* (2008) suggest a 'geographical dispersion' strategy to spread risks associated with single point of failure events, natural and anthropogenic events affecting the value stream (e.g. product contamination) or a node (e.g. damage to a facility). The authors cite Wal-Mart as a model resilient supply chain supported by a sufficient number of stores within reasonable proximity. An automated inventory management system identifies the location of needed resources, while trucks with onboard computers execute the shipments.

3.3 A Synopsis of Financial Risk Management Approaches

3.3.1 Introduction

According to finance literature, there are different motives for risk management. Reducing the firm's expected taxes, costs of financial distress and agency costs associated with debt and equity financing (Smith and Stulz, 1985), solving underinvestment problems (Froot *et al,* 1993), increasing debt capacity (Servaes *et al,* 2009) and adding value (Mackay and Moeller, 2007) are among such motives. These risk management motives are correlated to some extent. Reducing expected taxes increases the firm's cash flow, reducing financial distress costs increases the firm's value and increasing debt capacity allows the firm to raise more capital for new investments.

In this section, we focus on a number of financial risk management approaches that aim to eliminate or mitigate risks that have direct effects upon the operating cash flow of manufacturing firms. Our focus is consistent with the results of the survey of Servaes *et al* (2009), which identified maximizing of operating cash flow as a high priority item for the participating firms and of Bodnar *et al* (1995) which reveals that manufacturing firms rank second among all industries in the usage of derivatives.

Financial risk management approaches include the use of insurance policies, financial derivatives and foreign-currency denominated debt. Financial derivatives, which include forwards, futures, options and swaps, may be used with the objective of hedging or the objective of insuring the risk. Hedging is aimed at eliminating or minimizing the risk exposure at the expense of sacrificing any upside potential. Insuring the risk eliminates or minimizes the adverse consequences at the cost of an insurance premium. While forwards, futures and swaps are used as hedging instruments, options are used to achieve the insurance objective. Servaes *et al* (2009) reveals that most CFOs of participating non-financial firms use derivatives to manage risk. We discuss the use of derivatives in the following sections.

3.3.2 Risk Management Using Derivatives

3.3.2.1 Types of derivatives

A derivative is a "financial instrument whose value depends on (or derives from) the values of other, more basic underlying variables" (Hull, 2006). Japanese yen forwards, futures, and call and put options, for example, are derivatives whose underlying asset is the Japanese yen. The buyer (seller) of a Japanese yen forward contract has the obligation to buy (sell) a fixed number of Japanese yen at a particular date at a fixed exchange rate. Futures contracts are similar to forwards contracts with regards to the obligations of the buyer and the seller. While forward contracts are customized contracts whose terms are fixed by agreement between the buyer and the seller, and are said to trade over-the-counter (OTC), futures contracts are standardized contracts which are traded on futures exchanges. The buyer of a Japanese yen call (put) option has the right to buy (sell) a specified number of Japanese yen sometime in the future at a fixed exchange rate. A swap is an agreement between two parties to exchange a series of cash flows over the term of the swap. One series of cash flows could be fixed, and the other series could be floating, or both series could be floating. The floating cash flow is tied to an index such as an interest rate, currency exchange rate or the price of a particular commodity. Accordingly, swaps may be classified into interest rate swaps, currency swaps and commodity swaps.

A key feature distinguishing the derivative is the 'linearity' of the instrument (Froot *et al,* 1994; Tufano, 1996; Servaes *et al,* 2009). For example, the buyer (seller) of a forward contract is obliged to take (make) delivery of the underlying asset in exchange for a fixed delivery price. If the asset price rises (falls), the buyer (seller) makes a profit and vice versa. Hence, the payoff to the buyer (seller) is linearly dependent on the price of the underlying asset. This is also true in the case of a futures contract and a swap contract, under both of which the participants have certain obligations. This is not true in the case of options, however. A buyer of a call (put) option has the right to exercise the option on or before the expiration date and will do so only if the underlying asset price is higher (lower) than the option's exercise price. When the option is not exercised, the buyer loses only the premium price initially paid to purchase the option. When the option is exercised, the buyer makes gain. Hence, the payoff to the option buyer is non-linear. When the quantity to be hedged is unknown it is argued that a non-linear financial instrument provides better protection (Brown and Toft, 2002; Servaes *et al,* 2009). Another feature that distinguishes different derivatives is the characteristic of the market. While futures contracts are exchange-traded, forward contracts and swaps are OTC products, while options are traded both on exchanges as well as OTC (Bodnar *et al,* 1995). This feature shapes the cost structure of the instrument and hence influences the selection decision (Smith and Stulz, 1985; Froot *et al,* 1994; Servaes *et al,* 2009).

3.3.2.2 Use of derivatives in risk management

Financial derivatives are used by firms to manage exchange rate risk, interest rate risk and commodity price risk.

Exchange rate risk may be classified into transaction exposure, translation exposure and economic exposure. An example of transaction exposure is that of a Canadian manufacturer which procures some of its input components from Japan and is invoiced in Japanese yen. The manufacturer could hedge the risk of a rise in its input costs due to a rise in the value of the Japanese yen by buying a forward or futures contract on Japanese yen or buying a call option on Japanese yen. These derivative contracts would rise in value with the increase in value of the Japanese yen, allowing the manufacturer to offset the increased cost of the input components. An example of translation exposure is that faced by a firm which has a foreign subsidiary whose assets and liabilities are denominated in a foreign currency. As the foreign currency exchange rate changes, the consolidated financial statements of the parent firm, which are denominated in the parent's home currency, could record changes in the value of the assets and liabilities of the foreign subsidiary, even if these have not changed when denominated in the foreign currency. Finally, economic exposure to exchange rate changes arises if the sales of a company are threatened by changes in exchange rates. For example, a Canadian company with a Japan-based competitor could see its global sales decline if the Japanese yen declined in value relative to the Canadian dollar. Froot *et al* (1994) cite the case of Caterpillar, which saw its "real-dollar sales decline by 45% between 1981 and 1985" when the U. S. dollar increased in value, as an example of a U. S. exporter which could have benefited by using derivatives to hedge its exchange rate risk. It is generally agreed that transaction and economic exposure should be hedged, while translation exposure should be hedged only if the parent company intends to liquidate its foreign subsidiary. Servaes *et al* (2009) reported that 93% of the participating firms reported an exposure to exchange rate risk, while 82% of the firms use foreign exchange derivatives. Geczy *et al* (1997) find that the source of foreign exchange risk influences the type of instrument used. Firms with foreign operations tend to use forwards or a combination of forwards with either futures or options. The surveys by Servaes *et al* (2009) and Bodnar *et al* (1995) both reveal that forward contracts are the instrument of choice of responding firms, followed by swaps and then OTC options.

Interest rate risk arises from a mismatch between the maturity of a firm's interest rate investments and debt. For example, a firm's debt may have three months to maturity, while its investments may have five years to maturity. If the short term interest rate increases, the firm will suffer a loss (Triantis, 2000). This is an example of interest rate risk exposure. The company could hedge its interest rate risk by entering into an interest rate swap with a swap dealer, under which it receives interest payments based on the three month interest rate (floating rate) and makes interest payments at a fixed interest rate. A company's current and planned future positions in both borrowings and investments determine its vulnerability to the future change in interest rates (Bacon and Williams, 1976). 73% of the firms surveyed by Servaes *et al* (2009) reported having at least 10% of debt with floating interest rates, and 79% of the responding firms use interest rate derivatives. The most used derivative is the interest rate swap (Bodnar *et al,* 1995; Servaes *et al,* 2009).

Exposure to commodity price risk is not as common as the exposure to exchange rate risk and interest rate risk, but is still a key risk (Froot *et al,* 1994) and stems from possible changes in the price of input and/or output commodities (Unterschultz, 2000). For example, in January, a chocolate factory could take a long position in sugar futures contracts to hedge the price of sugar required for its November production. If the spot price of sugar increases in November, the factory could close out its futures position at a profit, which would offset the higher price that it would pay to buy sugar in the spot market. While 49% of the firms surveyed by Servaes *et al* (2009) reported exposure to commodity price fluctuations, and 32% of the firms use commodity derivatives, most of the firms tend to manage commodity price risk with non-financial approaches like contractual arrangements, pricing plans and natural hedges in addition to the standard OTC financial derivative contracts. Bodnar *et al* (1995) concluded that there is no financial derivative that dominates commodity price risk management. Instead, commodity price risk is hedged through a variety of financial contracts including swaps, options, futures and forward contracts (Bodnar *et al,* 1995; Carter *et al,* 2004). In their case study on fuel hedging Essaddam and Miller (2008) find that both futures contracts and futures options are effective in managing price risk.

3.3.2.3 Limitations in using derivatives

There are several limitations in using derivatives to manage risk. Firstly, not all assets have corresponding derivatives. For example, there are no futures contracts on jet fuel, which has led airlines to use heating oil futures to manage the price risk of jet fuel. Secondly, the effectiveness of the instrument in hedging risk depends on the correlation between the movements in the price of the asset which is being hedged and the asset underlying the futures. In the case of airline jet fuel hedging, this is the correlation between changes in the price of jet fuel and the price of heating oil. Such a correlation may not always be high enough to make the derivative as effective as desired. Thirdly, the fixed size of the derivative contract may create difficulties in formulating the perfect hedge. For example, the Japanese yen futures contract traded on the Chicago Mercantile Exchange Group has a size of 12.5 million yen, making it difficult to hedge an exposure of 15 million yen. Fourthly, it is possible that a multinational company anticipates that it will have foreign sales denominated in foreign currency, but has no idea of the magnitude of these sales. Finally, exchange-traded derivatives have specific delivery/expiration dates that may not coincide with the date of the anticipated transaction that a firm wishes to hedge. Furthermore, the price of the hedge can be a severe impediment and as such may discourage hedging in certain cases.

3.4 Distinctions between Operational and Financial Risk Management Approaches

While operational and financial risk management approaches share a common objective, which is to protect firms from the negative impact of various risks, such approaches also have a number of differences. In the following sub-sections, we describe the major differences which have been highlighted by the reviewed articles. We initially focus on time horizon and cost. Next, we highlight the differences in their impacts on firm's performance and risk exposure. Finally, we present the arguments that characterize operational and financial approaches as substitutes or complements.

3.4.1 Time horizon

The effects of some financial risk management approaches are largely limited to short term (Chowdhry and Howe, 1999; Aabo and Simkins, 2005), but do not provide the firm with the strategic position to sustain its competitive edge on a long term basis. For firms exposed to exchange rate risk, use of financial derivatives can mitigate the short term impact of transaction risk but do not prevent the long term effects of competitive risk (Triantis, 2000). In addition to the direct transaction advantage, some competitors can also exploit the change in demand for the firm's product as the exchange rate has a direct correlation with the demand for imported products. Unlike financial contracts that have short term effects on risk exposure, the operational approaches, as discussed in Section 3.2, are implemented to protect the firm from long term risk exposures (Dufey and Srinivasulu, 1983; Chowdhry and Howe, 1999; Carter *et al,* 2001; Kim *et al,* 2006, among others). At a point in time, many airlines had increased their fuel price hedging horizons to an unprecedented period of six years, as demonstrated in the case of Southwest Airlines (Carter *et al,* 2006).

3.4.2 Cost

The long term competitive advantage achieved by employing operational risk management approaches is associated with high costs incurred in opening and closing production facilities, changing product and process designs and many other operational options. The cost of financial hedging (for example, the transaction cost of currency hedging) is much lower than the cost of operational approaches (for example, the costs involved when opening a new production facility in a foreign country) (Chowdhry and Howe, 1999; Triantis, 2000; Hommel, 2003). Operational approaches tend to be very costly due to their strategic nature and firms may opt to implement lower level tactical approaches to avoid such costs. In their survey of non-financial Danish companies, Aabo and Simkins (2005) found that 54% of the surveyed companies would shift their sourcing among suppliers to manage their exposure to the currency rate, compared to only 25% that would take a more permanent action by opening or closing a production facility. However, operational approaches can be cost effective when implemented by firms that are part of a global network with diversified operations (Carter *et al,* 2001). Such approaches could be less costly than financial derivatives if the exchange rate volatility or the planning horizon increases (Triantis, 2000; Hommel, 2003). In this context, Huchzermeier and Cohen (1996) argue that as the time horizon gets longer, the cost of financial tools increases while the cost of operational approaches decreases.

3.4.3 Impact on business performance

The implementation of high cost operational approaches can be justified by the significant positive impact on the firm's performance. Huchzermeier and Cohen (1996) develop a model to value operational flexibility (the options of switching among production plants and / or supply channels) in terms of the improvement in the expected after-tax profit a firm can achieve after exercising such options (see also Kogut and Kulatilaka, 1994). The increase in expected profits would consequently result in an increase in the firm’s value (Hommel, 2003). The impact of the capacity allocation option on the firm’s performance is studied by Ding *et al* (2007). By exercising the capability to postpone foreign demand to avoid the adverse effects of the exchange rate change, the firm improves its expected profit and minimizes the exposure risk. This improvement in the firm’s profit due to operational flexibility and capacity allocation options seems to be a common impact of operational approaches as argued by Chowdhry and Howe (1999). The authors believe that this impact on profits cannot be achieved by financial hedging contracts alone. This conclusion is supported by Huchzermeier and Cohen (1996). Through a global manufacturing supply chain network model, Huchzermeier and Cohen (1996) found that financial hedging against exchange rate risk does not make a significant change in the expected after-tax profit of the firm. Although Ding *et al* (2007) agree that financial tools do not directly increase the firm’s profit, they point to the indirect impact of these tools. The authors argue that decreases in the variability of profits caused by financial contracts would motivate firms to invest in more capacity that provides a potential for profit increases.

While the implementation of operational flexibility is shown to increase the firm’s value, there are inconsistencies in the findings of empirical studies on the relation between financial hedging and firm’s value as observed by Carter *et al* (2006). In a theoretical study, Smith and Stulz (1985) explain how hedging should increase firm value. This is confirmed in the empirical study by Allayannis and Weston (2001) who reveal a positive relationship between hedging and firm value. Similarly, Carter *et al* (2006) find that financial hedging increases firm values in the airline industry. However, Triantis (2000) contends that operational approaches are better strategies to increase firm value. This perspective is supported by the empirical results of Kim *et al* (2006) where the added value due to operational tools was found to be higher than that due to financial instruments. While the positive effects of the financial tools on the firm's value and profit are argued to be of some significance, the negative effects of the downside risks associated with these tools may prove to be more significant. Huchzermeier and Cohen (1996) argue that the financial hedging tools would have adverse consequences on the firm's ability to enter new markets due to the predictability of its cost structure. Another negative effect can occur when a company decides to hedge fully (say against exchange rate or commodity price risk) resulting in an inability to make value-enhancing moves (Froot *et al,* 1994).

3.4.4 Downside risk, upside potential and uncertainty exploitation

While the positive impacts of operational and financial approaches on firm performance are important, the primary objective of these two approaches is to reduce the firm's risk exposure. While both approaches are efficient in reducing exchange rate risk (Carter *et al,* 2001; Kim *et al,* 2006), forward contracts deprive the firm of the upside potential in order to eliminate the downside risk (Huchzermeier and Cohen, 1996; Triantis, 2000). For example, an exporting firm takes a short position in a forward contract on the foreign currency-denominated revenue that the firm expects to receive on a future date, to protect against a possible depreciation of the foreign currency. However, in case of depreciation of the home currency, the exporting firm loses the opportunity to profit as it is bound by the contract to sell the foreign currency at the forward rate rather than the now favorable spot rate. Blume (1971) and Moore (1983) emphasize that upside potential motivates one to take a certain risk in the first place. The loss of the opportunity to increase the cash flow can be costly if, for example, the exporter in the above example has to raise new capital to finance a promising investment (Servaes *et al,* 2009).

Operational approaches not only reduce risk, but also exploit the uncertainties underlying these risks to increase firm's value (Triantis, 2000; Ding *et al,* 2007). Triantis (2000) provides an example of a manufacturer with overseas sales. When the home currency appreciates, the manufacturer experiences a decrease in its cash flow. By operating a production facility in a foreign country, the manufacturer can avoid the decrease in the cash flow by ensuring that costs and revenues are denominated in the same currency. This allows the manufacturer to outperform its competitors who do not have production facilities in that foreign country. While Huchzermeier and Cohen (1996) consider uncertainty exploitation to be exclusive to operational approaches, Carter *et al* (2006), among others, explain how financial hedging tools can also exploit uncertainty. Airline companies that efficiently hedge fuel prices can sustain their projected cash flow during "periods of distress" in which fuel prices are high, which provides them the opportunity to acquire weaker firms. In a survey on non-financial companies, 17% of CFOs find that risk management allows exploitation of trading opportunities in foreign exchange, interest rates and commodities (Servaes *et al,* 2009).

3.4.5 Substitutes or complements

Researchers on integrated risk management provide arguments to support operational and financial risk management approaches as both substitutes and complements. Hommel (2003) describes operational diversification as a substitute for financial derivatives when the asset to be hedged and the time horizon are not matched by available derivatives. Aabo and Simkins (2005) report that 52% of the non-financial firms surveyed believe that currency exposure should be managed by operational approaches rather than by financial instruments. Mello *et al* (1995) study two cases of risk management and find that the number of financial hedging contracts decreases when the firm's operational flexibility increases in one case and decreases in the second case. A positive correlation between operational diversification and financial hedging is also observed in Allayannis *et al* (2001) and Kim *et al* (2006). Chod *et al* (2010) study the relationships between two types of operational flexibility and financial hedging under uncertainty in demand for two products. Although the authors find postponement flexibility and financial hedging to be substitutes, the relationship between product flexibility and financial hedging is found to depend on the correlation between the demands for the two products. The two approaches are complements when demands are positively correlated and substitutes when the demands are negatively correlated.

3.5 Integrated Operational and Financial Approaches

The differences between operational and financial risk management approaches in terms of cost, time horizon, firm performance and risk support the need to integrate these two approaches to counterbalance the shortcomings of one approach by the benefits of the other. For example, limitations of financial instruments in reducing competitive risk can be overcome by a strategic operational initiative. The high cost of operational approaches can be alleviated by exploiting low cost financial instruments which are equally effective. In addition, operational and financial approaches can, when combined, manage risks that cannot be managed by a single approach. Firms are continuously exposed to a bundle of risks that cannot be reduced by financial instruments alone (Miller, 1992), but can only be managed by an integrated approach. We highlight these possibilities in the following review of the rather scanty literature on integrated operational and financial risk management approaches.

Weiss and Maher (2009) examine the effects of fuel hedging by focusing on the hedging capability of nine U.S. airline companies. The results show that fuel hedging does not significantly contribute to the firm's hedging capability. The authors justify this finding by arguing that fuel hedging cannot protect airline companies against variations in demand for airline services. This demand uncertainty is one of the various operating problems that cannot be effectively tackled by financial instruments alone (Aabo and Simkins, 2005). Chowdhry and Howe (1999) argue that a financial hedging tool can be effective in hedging exchange rate risk if demand is deterministic. It is therefore reasonable to conclude that in the case of uncertain demand, exchange rate risk should be managed by an integrated operational and financial approach.

Financial derivatives support the implementation of operational approaches. Allayannis *et al* (2001) and Faseruk and Mishra (2008) conclude that operational hedging in the form of geographical dispersion does not protect multinational firms from exchange rate risk unless it is in addition to the use of currency derivatives and foreign debt. Triantis (2000) presents an example of a manufacturer who uses his production switching capability to mitigate his exposure to currency fluctuations. If the home currency depreciates, currency derivatives can offset the reduction in value of the overseas facility. Hommel (2003) describes such use of financial instruments as a 'buffer' for the implementation of operational approaches. Dufey and Srinivasulu (1983) explain that hedging eliminates risks of unexpected changes in the exchange rate, allowing operational approaches to deal with variations in business activity. The implementation of financial tools would also have an impact on operational decisions. Gaur and Seshadri (2005) demonstrate how financial hedging allows a retailer to increase its optimal inventory level for a product when the demand for that product is correlated with the price of the asset underlying the financial instrument.

The complementary effects of operational and financial approaches make the integrated implementation of these approaches more valuable than their separate implementation. Carter *et al* (2001) report that the integrated approaches reduce the firm's risk exposure more effectively due to the ability to manage both long and short term risk exposure. Ding *et al* (2007) show that the simultaneous use of currency options and the capacity allocation options result in better performance measures than the use of each tool separately. Mello *et al* (1995) find that firm value is highest when operational flexibility is high and financial hedging is used. Faseruk and Mishra (2008) argue that not only does the integrated strategy increase firm value, but that the utilization of a single approach in an isolated manner may not even increase the firm's value at all. This is consistent with an earlier finding by Miller (1992) who argued that the implementation of one approach would give 'suboptimal' results since the two approaches are interrelated.

We summarize in Table 3.5 the various combinations of operational and financial approaches along with the type of risk under which these combinations have been applied in the literature.

3.6 Areas for Future Research

Table 3.5 facilitates making some observations as to the current state of the integrated SCRM literature. Exchange rate risk exposure is mostly incorporated in the models reported and most models use currency derivatives. As discussed in Section 3.3, commodity price risk and interest rate risk are also key risks to be managed. Hence, new models need to be developed to further incorporate these risks in integrated SCRM modelling. On the operational side, most often, three types of operational approaches (geographic dispersion, switching production and capacity allocation postponement) are integrated with financial instruments. Considering the large number of available operational strategies which were discussed in Section 3.2, the research opportunities of integrating these other operational approaches (such as, inventory management) with financial instruments could be substantial. The reviewed quantitative models tend to focus on downstream operations and mostly involve manufacturing plants and those markets in which they sell. Designing models that also incorporate the upstream partners of a firm could narrow this gap in the literature. It is also observed that the reviewed models have the common objective of optimizing a firm's performance and hence are very much focal firm centric. As argued by Juttner *et al* (2003) and Rao and Goldsby (2009), among others, the objective of supply chain risk management is to reduce the vulnerability of the supply chain as a whole rather than of the focal firm. While building models that improve the performance of a supply chain as a whole could be challenging, the models would significantly contribute to developing novel risk management strategies that could provide contemporary supply chains a competitive edge.

Table 3.1 Risk management approaches for the risk domain 'internal operations'

Sources of Major Risks	Identified Risks	Risk Management Approach			Functional Area(s)
		Avoidance	Prevention	Mitigation	
Process uncertainty	Products causing safety hazards (109)		Vendor selection, supply chain visibility (109)	Reverse logistics: efficient transportation strategies, modal flexibility (109)	Sourcing , Logistics , Information Systems (109)
	Machinery / equipment breakdowns (105)			Improve flexibility (105)	Manufacturing (105)
	Capacity / time / quality (36, 104)	Real options: defer, outsource, scale down, abandon (36)	Real options: stage, explore, lease, growth (36)	Flexible process strategy via flexible manufacturing process (104)	Process Design (104), Strategy (36)
	Delivery / processing delays (94)			Conversion flexibility (94)	Process Design (94)
	Lead time uncertainty (10)		Model based decision support system (10)		Manufacturing, Procurement (10)
Information system failures	Information delays / disruptions (36, 57)	Real options: defer, outsource, scale down, abandon (36)		Conversion flexibility (94)	Strategy (36), Information Systems, Sourcing, Manufacturing (57)
Labor uncertainty	Labor strikes, employee turnover (57, 94)				

Table 3.2 Risk management approaches for the risk domain 'external stakeholders'

Sources of Major Risks	Identified Risks	Risk Management Approach			Functional Area(s)
		Avoidance	Prevention	Mitigation	
Supplier reliability	Quality / delivery reliability (36, 86, 104, 102, 105)	Real options: defer, outsource, scale down, abandon (36)	Supply network design (102); Alignment of strategy with relationship (94, 102); Supplier selection process (102,); Supplier certification programs (49, 72, 79, 105); Backward integration (63, 72)	Build up redundancies: safety stocks, multiple suppliers (105); Supplier order allocation: sourcing mitigation / contingent rerouting / inventory mitigation / acceptance (106)	Sourcing (102), Strategy (36, 102), Supply and Procurement (94)
	Business continuity (84, 102, 105); Risk of particular segment of supply chain being crippled (9)		Supplier selection process (102)	Disruption recovery strategies: Supply chain reconfiguration / Supply chain redesign (9)	Sourcing (75, 102), Strategy (9)
	Supply yield / capacity uncertainty (102)		Supply network design (102); Alignment of strategy with relationship (11, 34, 50, 81, 94, 102); Supplier order allocation (102)		
	Lead time uncertainty (102)				
	Price uncertainty (6, 102, 104)			Flexible supply strategy via multiple suppliers (104)	Sourcing (102)
	Commitment (104)			Flexible (time-based) supply contracts (102, 104); Supplier order allocation (104)	Sourcing (104)
Distribution	Shipment disruptions (inbound / outbound) (94)		Ability of information systems to detect disruption and take corrective action (94); Disruption discovery strategies: predictive analysis: intelligent search agents, dynamic risk index tools (9)		Information Management (94)
Network	Chaos, lack of ownership, inertia (57)		Control strategies (57)		Operations (57)

Table 3.3 Risk management approaches for the risk domain 'marketplace'

Sources of Major Risks	Identified Risks	Risk Management Approach: Avoidance	Risk Management Approach: Prevention	Risk Management Approach: Mitigation	Functional Area(s)
Uncertainty in demand	Volume (102, 104)	Focus on products with constant demand and few variants; Focus on secure markets (105)	Shifting demand across time: advance commitment discount program (102)	Price postponement strategy / shifting demand across time, revenue/yield management, delivery postponement (102); Flexible supply strategy via flexible supply contracts (102, 104)	Manufacturing / Product Differentiation (104), Demand Management (102)
	Mix (102, 104, 117)		Shifting demand across products: product substitution/product bundling (102)		Demand Management (102)
	Price (37, 38, 102)			Flexibility of production assets (1, 38)	Sourcing (102), Finance (38)
	Contract uncertainty (87); Cancellation risk			Operational flexibility, contractual flexibility (87)	Demand Management, Manufacturing (87)
	Rapid change in technologies and product markets (36); Short product life cycles (36, 94, 102, 117); Customization (94, 100, 111, 117)		Shifting demand across markets: product rollover strategy (102); Real options: lease, explore, scale up (36); Contract flexibility (111)	Financial hedging: options contract (111) ; Flexible pricing strategy via responsive pricing (104); Flexible product strategy via postponement (102); Postponing product differentiation via standard components, modular design, postponement of operations, re-sequencing of operation (102); Postponement strategies: product development postponement, production postponement, purchasing postponement, logistics postponement (94, 117)	Demand Management (102), Strategy (36), Sourcing (111), Finance (111), Manufacturing (100, 102, 104, 117), Product Design (100, 117), Logistics, Distribution/marketing (45, 100)
	Information (9, 94, 100, 102, 105); Bullwhip effect (102)		Information management strategies: quick response system, information sharing, vendor managed inventory, collaborative forecasting (102); Disruption discovery strategies: improving transparency, information availability within the supply chain, e.g. RFID, tracking and tracing devices (9, 105); Cooperation strategies (57); Capacity visibility at different nodes (9); Use of ERP for managing global operations, improving supply chain agility (100)	Improving supply chain flexibility (100)	Information Management (9, 100, 102, 105), Sourcing (57, 100, 105)
Currency exchange rate fluctuation	Transaction risk (61, 107)		Supplier order allocation (102)	Operational flexibility (option value of excess capacity) (53, 65, 96, 102); Flexibility in sourcing (1, 87); Futures, forwards and options (1, 2, 3, 13, 27, 37, 45, 51, 53, 61, 75, 91, 107)	Sourcing (102), Strategy (65, 102), Finance (53, 65, 75)
	Translation risk (107)				
	Competitive risk (36, 61, 107)	Real options: defer, outsource, scale down, abandon (1, 36)	Real options: stage, explore, lease, growth (1, 36)	Geographic diversification (20, 51, 61)	Strategy (36)
Marketplace randomness	Fluctuations in prices of finished products, raw materials, labor, energy, interest rate (13, 63, 91, 107)			Supply chain network design: resource flexibility mechanism, shortage response actions (63); Futures, forwards, options and swaps (4, 13, 21, 22, 40, 54, 91, 110)	Strategy (63)

Table 3.4 Risk management approaches for the risk domain 'environment'

Sources of Major Risks	Identified Risks	Risk Management Approach			Functional Area(s)
		Avoidance	Prevention	Mitigation	
Natural disasters	Hurricanes, floods, earthquakes, forest fires (57, 63, 94, 105)	Resilience strategies: closing facilities, delaying implementation, outsourcing (63); Geographical avoidance (57, 105)	Employee empowerment / top level involvement (94)	Supply chain network design: responsiveness policies: resource flexibility mechanisms, shortage response actions, Resilience strategies: building up flexibilities and redundancies (63), Geographical dispersion (84, 86)	Change Management (94), Sourcing, Production, Inventory Management, Logistics (63)
Major accidents	Epidemics, chemical/nuclear spills-product contamination (57, 63, 86, 105)				Strategy (86)
Political / sociopolitical conditions	Instability of the geographical area (63)			Investing in flexible / redundant network structure (63)	Strategy (57, 63, 105), Logistics (63)
Willful attacks	Terrorist attacks, political coup (57, 63, 105)				
Regulations	Financing, taxation, regional trading zones, local content rules (36, 102)	Real options: defer, outsource, scale down, abandon (36)	Supply network design (102)		Strategy (36, 102)
	Regulations affecting product development / product launching (36)	Real options: defer, outsource, scale down, abandon (36)			Strategy (36)

Table 3.5 Risks managed by integrated operational and financial approaches

	Risks managed by integrated operational and financial approaches				
Operational / Financial	Geographic dispersion	Switching production	Capacity allocation postponement	Inventory management	Operational options (various)
Financial hedges (various)	Exchange rate (41)			Inventory risk due to demand uncertainty (44)	Exchange rate (1), Severe disruptions (113)
Currency derivatives (various)	Exchange rate (3, 20, 61)	Exchange rate / demand (27)	Exchange rate / demand (37)		
Currency forwards	Exchange rate (51)	Exchange rate (75)			
Currency options		Exchange rate (51)			
Exotic derivatives			Exchange rate (114)		
Foreign debt	Exchange rate (3)				Exchange rate (14)

Chapter 4

Integrated SCRM Model via Operational and Financial Hedging

4.1 Introduction

Risk management provides a long-sought arena to visualize and understand the true nature of supply chain management: its interdisciplinary context. As risk management in business spans several disciplines such as procurement, finance, operations and marketing, the approaches used to manage risks along a supply chain need to be interdisciplinary as well. As reported in a large number of articles on supply chain risk management that appeared over the last decade (Chapter 2), studies using interdisciplinary and integrated approaches to supply chain risk management (SCRM) have recently gained momentum.

This Chapter contributes to research on SCRM by examining an integrated approach to risk management using operational and financial hedging methods. The application venue considered is the beer industry with three members along its supply chain: an aluminum can supplier, a brewery and a beer distributor. Faced with beer demand uncertainty and volatile aluminum prices, a simulation based optimization model is developed incorporating both operational and financial risk management techniques. The operational hedging technique focuses on timing and quantities of aluminum sheet procurements as well as inventory levels of raw material, work in process and finished goods maintained at all three supply chain members. The financial hedging technique focuses on the optimal purchase of call and put options on aluminum futures to hedge aluminum price uncertainty. The integrated model minimizes the expected total opportunity cost of the three supply chain members over the eight week peak demand period.

Section 4.2 reviews previous research on integrated operational and financial risk management. Section 4.3 presents a conceptual background to our study which focuses on problem setting and the model framework. Section 4.4 discusses the risk management processes used in the integrated risk management model. Section 4.5 describes the integrated risk management model in detail. Section 4.6 discusses a sequential model which first applies operational hedging techniques to determine the optimal purchase quantities of the input commodity (aluminum) and inventory levels maintained by the different members of the supply chain, and then applies financial hedging techniques to determine the optimal purchase quantity of call and put options on aluminum futures contracts. Section 4.7 presents the experimental design used for the simulation based optimization. Section 4.8 discusses the results. These reveal that, in most of the cases addressed, the integrated model significantly outperforms the sequential model in minimizing the expected total opportunity cost. Section 4.9 presents conclusions and offers areas for further research.

4.2 Literature Review

Due to the limitations inherent in the individual approaches, research on integrated operational and financial approaches to manage risk is recently attracting more interest from researchers and practitioners alike. For example, firms exposed to exchange rate risk can use financial derivatives to manage the short term impact of transaction risk but cannot affect the long term effects of competitive risk (Triantis, 2000). Through a survey, Servaes et al (2009) report that 63% of the participating companies recognize the benefits of enterprise risk management. Previous studies such as those of Miller (1992) and Carter et al (2001) conclude that managing risk on a firm level is more effective than managing it on a functional level. Companies may even incur losses when individual functional divisions attempt to implement risk management approaches in isolation from other departments. Proctor & Gamble and Metallgesellschaft suffered catastrophic losses after they assumed positions in financial derivatives that were not consistent with their firm's corporate strategy (Froot et al 1994). In Chapter 3, we report in our review on operational, financial and integrated models that the results of a number of models which integrate operational and financial approaches support the above arguments. In what follows, we review studies on theoretical models of integrated operational and financial approaches as well as empirical studies.

4.2.1 Theoretical Models

The real options approach provides operational flexibility by allowing the firm to switch production between plants located at different countries to supply various markets (Kogut and Kulatilaka 1994, Huchzermeier and Cohen 1996). Just as currency options do, the real options approach allows the firm to protect itself against fluctuations in a currency exchange rate. The use of real options is integrated with the use of financial instruments in models developed by Mello et al. (1995), Chowdhry and Howe (1999) and Hommel (2003) to mitigate risks arising from demand uncertainty and varying currency exchange rates. For a firm which issues foreign-currency denominated debt to hedge foreign currency risk, Mello et al. (1995) discern a relationship between the firm's liability structure and its operational flexibility. Chowdhry and Howe (1999) find that production flexibility can be used to hedge foreign currency cash flows. Hommel (2003) distinguishes between two operational hedging strategies: diversification and flexibility. While diversification involves choosing the firm's currency mix, flexibility allows the firm to alter this mix by switching production between plants according to observed changes in the currency exchange rate. The above models assume that the plants among which production can be switched always possess sufficient capacity. However, this assumption may not be realistic. Ding et al. (2007) assume that production capacity is limited and that the real option available to the firm is to postpone capacity allocation. Upon the realization of the demand for the firm's output and of the currency exchange rate, the firm decides how much capacity to allocate to each market. The model determines the optimal capacity and the optimal position in foreign currency options that maximize the firm's expected profit and minimize the variance of profit.

The above models employ financial instruments to hedge against exchange rate changes, while the risk arising from output demand uncertainty is mitigated by operational flexibility. However, Chod et al. (2010) use financial tools to hedge against demand uncertainty. These authors examine the relationship between financial hedging and two forms of operational flexibilities: product choice and postponement of production. Product choice allows a firm to produce two different products with the same resource while the ability to postpone production allows the firm to delay production completion until demand is realized. These authors show that while postponement flexibility is a substitute for financial hedging, product flexibility and financial hedging can be either complements or substitutes depending on the nature of the correlation between the demands for the two products. Gaur and Seshadri (2005) also use financial instruments to hedge against demand uncertainty They assume that demand is correlated with the price of the asset underlying the financial instrument and argue that the degree of this correlation influences hedging benefits. Their model determines an optimal inventory level and hedging strategy to maximize expected profit and minimize its variance.

4.2.2 Empirical Studies

Some empirical studies shed light on the benefits of integrating operational and financial hedging strategies. In their studies of multinational and non-financial firms, Allayannis et al. (2001), Kim et al. (2006) and Carter et al. (2001) find that geographical dispersion of a firm's activities is an operational hedging strategy that is complemented by the use of currency derivatives to hedge against foreign exchange risk. Other operational hedging strategies include the real options of switching production, entering new markets and changing suppliers. Aabo and Simkins (2005) address the relationship between real options and financial hedging in managing foreign exchange risk and find that a majority of the surveyed firms do not use financial instruments to hedge this risk, but would rather manage the firm's exposure with real options.

4.3 Conceptual Background

4.3.1 Problem Setting

A brewery purchases aluminum cans from a can supplier, produces canned beer and then transports it to a distribution center which maintains an inventory of canned beer to meet retailers' demand. The supply chain, which consists of the aluminum can supplier, brewery and beer distributor, faces risks which originate from upstream and downstream. The can supplier, using aluminum sheets as the major material input for can production, faces aluminum price volatility, while the distribution center faces uncertainty in beer demand. Aluminum price volatility causes fluctuations in packaging cost while beer demand uncertainty causes either a shortage or a surplus in finished goods inventory. Firms can hedge commodity price uncertainty with financial hedging approaches, such as the use of commodity futures and options, and manage demand uncertainty with various operational hedging approaches, such as the use of rigorous forecasting methods and inventory management systems. We develop a model to capture the benefits of integrating operational and financial hedging approaches to manage the risks of aluminum price volatility and beer demand uncertainty.

4.3.2 Model Framework

The model assumes a partnership-like relationship among the members of the supply chain. In this vein, we assume that information on the demand at various stages across the supply chain is not distorted and that it flows in a timely manner across the supply chain. The beer industry faces a seasonal demand, characterized by highs in summer and lows in winter. Our model focuses on the supply chain's financial and operational decisions pertinent to a period of eight weeks of peak demand during summer. The major breweries produce a variety of brands, all of which are packaged in the same type of aluminum can with different labels. We consider in our model the aggregate demand of all brands.

The model incorporates inventory levels of three items: canned beer at the distribution center, empty aluminum cans at the brewery and aluminum sheets at the can supplier. While the inventories of aluminum sheets and canned beer are physically maintained and managed solely by the can supplier and the distribution center, respectively, the inventory of empty aluminum cans requires a close coordination between the brewery and the can supplier. The empty cans could even be stored in a third party warehouse.

The integrated model minimizes the expected total opportunity cost, E(TOC), of the supply chain as a whole, rather than merely minimizing the opportunity costs of one of the supply chain members. The total opportunity cost includes: i) inventory carrying costs at all stages of the supply chain, stock-out costs emanating from the mismatch between demand for beer and the inventory of canned beer, and ii) costs associated with hedging aluminum price volatility with inventory and with options on aluminum futures. Our model builds on the premise that the decisions on aluminum and canned beer inventories need to be made in an integrated manner to minimize the expected total opportunity cost while maintaining the value at risk (VaR) of total opportunity cost within a predefined limit. The VaR limit is incorporated in the model as a constraint and its value depends on the level of risk aversion of the supply chain, to be collectively agreed upon by the supply chain members.

4.3.3 Supply Chain Risk Management Process

Figure 4.1 presents the chronology of the risk management process used by the supply chain. In the figure, 'w' is used to represent a week, 'T' is used to represent a time period that can span a number of weeks, and 't' represents a point in time, that is, the beginning of a week. All decision variables and some parameters in the model are associated with inventory type and/or a point in time. For these variables and parameters, we use two subscripts, i and j, where i = {a, b, c} denotes **a**luminum sheets, canned **b**eer and empty **c**ans, respectively, and j = {0, 1, …, 13} represents a point in time.

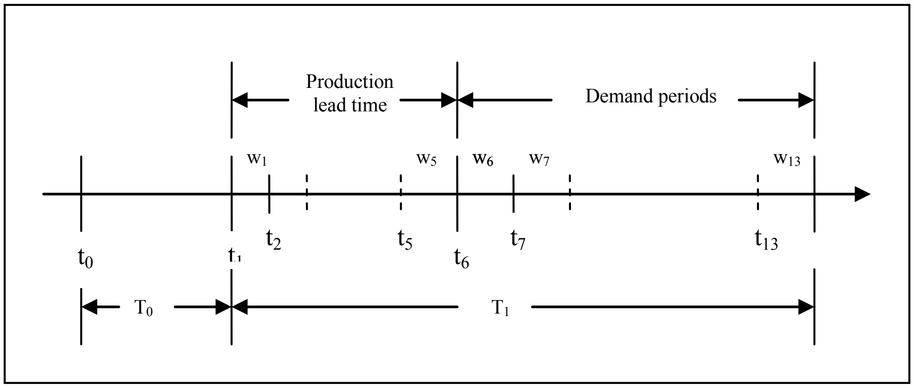

Figure 4.1 Chronology of the risk management process

4.3.3.1 Hedging Aluminum Price Risk Uncertainty with Inventory and Options on Aluminum Futures.

Time t_0 represents the current point in time at which the can supplier places an order for aluminum sheets. These are required to produce a portion of the cans needed by the brewery to satisfy the beer demand anticipated to occur during the final eight weeks of a future time period T_1. The time period $T_1 = \{w_1 \ldots w_{13}\}$ spans 13 weeks. The first five weeks of T_1 are reserved for the lead time L_c required by the can supplier to produce empty cans (4 weeks) and the lead time L_b required for the brewery to produce beer (1 week). Faced with aluminum price variability and uncertain demand for beer, the supply chain needs to make two strategic decisions on: i) the quantity of aluminum sheets to procure (Q_a) and ii) the effective price to pay for the aluminum. The can supplier and the brewery make their decisions based on their mutual interest of optimizing the supply chain performance, defined as the minimization of the expected total opportunity cost along the supply chain over the total time span T_0 and T_1.

At time t_0, the can supplier purchases an initial quantity of aluminum Q_{a0} from the spot market at the spot price of S_0 per unit. This purchase is a hedge against future increases in the aluminum price. As the future demand for beer is revealed, and hence the future demand for aluminum cans, it is possible that the initial quantity of aluminum purchased is higher or lower than the quantity which is actually needed, thereby resulting in holding costs or stock-out costs. At time t_1, the can supplier purchases a second quantity of aluminum Q_{a1} from the spot market at a spot price S_1. The purchase of aluminum in two batches reduces the total holding costs associated with holding aluminum sheets in inventory and allows time for the buyer to respond to price changes in the market place since time t_0.

Considering the initial quantity of aluminum purchased at t_0, if the aluminum price were to decline in the future, then the supply chain would incur an opportunity cost, since by waiting to purchase aluminum, it could have done so at a lower price. To offset the opportunity cost associated with aluminum price decreases, the can supplier buys at t_0 a number N_p of European put options on aluminum futures with a premium p_0, an exercise price K and expiration date t_1. The put options are assumed to be at the money at purchase such that the exercise price K is equal to the underlying aluminum futures price F_0 at time t_0. It is also assumed that the delivery date of the underlying futures contract coincides with the options' expiration date t_1.

At time t_1, if the observed aluminum spot price S_1 is lower than the spot price S_0 on the initial date t_0, then the present value of the opportunity cost associated with the initial purchase of aluminum is given by $Q_{a0}(S_0\text{-}S_1e^{-rT0})$, where r represents the weekly risk free interest rate. The futures contract price F_1 should be equal to S_1, since the spot and futures price should converge on the futures contract's delivery date. As the options are at the money on purchase so that $F_0 = K$, hence $F_1 < K$. In this case, the can supplier exercises the options, resulting in a payoff equal to $N_p(K-F_1)$, which offsets the opportunity costs associated with the purchase of the initial quantity of aluminum. However, if S_1 is greater than S_0, the initial purchase of aluminum at a lower price provides an opportunity gain. In this case $F_1 > K$, so the put options will be left to expire unexercised.

Considering the second quantity of aluminum sheets (Q_{a1}) purchased at time t_1, the supply chain would incur an opportunity cost should the aluminum price increase. To offset this latter cost, at t_0, the supplier buys a number N_c of European call options on aluminum futures at a premium c_0, an exercise price K, and expiration date t_1. As with the put options, the call options are assumed to be at the money so that $K = F_0$. It is also assumed that the delivery date of the underlying futures contract coincides with the options' expiration date t_1.

Associated with the decision to postpone a portion of the aluminum quantity purchase Q_{a1} to t_1, an opportunity cost is incurred if the aluminum spot price S_1 is higher than its initial value S_0. This cost is given by $Q_{a1}(S_1e^{-rT0}-S_0)$. In this case, $F_1 = S_1 > K$, and the can supplier exercises the call options with a payoff equal to $N_c(F_1-K)$, which offsets the opportunity cost associated with the postponement of the aluminum purchase. On the other hand, if the aluminum spot price S_1 decreases below its initial value S_0, the decision to postpone the purchase of a quantity of aluminum to t_1 results in an opportunity gain. In this case, the call options will be left unexercised.

4.3.3.2 Production Schedule and Inventory Flows

To manage the demand occurring over time span T_1, the supply chain members maintain appropriate levels of the three inventory types in order to maximize the fill rate while minimizing holding costs. The lead times L_c and L_b are considered in scheduling production lots. Inventory flows are determined using pull logic with estimated beer demand as the starting point.

As an example, the following illustrates typical decision sequences corresponding to beer demand in week 6. This is the first demand period in our planning horizon. The same applies to all other weekly demands. The brewery estimates the demand d_6 that would be realized over week w_6 and accordingly ships a quantity of beer Q_{b6} to the distribution center so as to have a beginning inventory B_{b6} ready to fill customers' orders over week 6. The brewery starts to fill and pack a corresponding quantity of beer cans P_{b5} at time $t_5 = t_6 - L_b$. Empty cans are transferred from the warehouse in which a beginning inventory level of empty cans B_{c5} is replenished by an incoming quantity of empty cans Q_{c5} from the can supplier. After transferring Q_{c5} to the canning process the warehouse's empty can inventory level drops to the ending value E_{c5}, to be transferred to the next week. To dispatch Q_{c5} on time, the first lot of can production P_{c1} at the can supplier starts at t_1, where $t_1 = t_5 - L_c$. The quantity of aluminum sheets required to produce P_{c1} is transferred from the beginning aluminum sheets inventory B_{a1} at the can supplier, which equals the sum of the aluminum quantities purchased at t_0 and t_1. Following the transfer, an inventory level E_{a1} remains on hand at the can supplier ready to be used during the following weeks.

At the start of week j, as demand for canned beer d_j starts being realized, the distribution center satisfies this demand from available inventory B_{bj} ending up with remaining inventory E_{bj}. The total quantity of canned beer distributed during the week is M_{bj}. If $B_{bj} < d_j$, the supply chain incurs a stock-out cost (s). On the other hand, if $B_{bj} > d_j$

the surplus quantity is carried over to the next week, incurring a unit weekly holding cost (h'_b).

Our model determines the optimal inventory levels by controlling the flows among the three inventory types of canned beer, empty cans and aluminum sheets. Subject to associated lead times, beer inventory is to be kept to a minimum level, while inventories of unprocessed aluminum sheets and empty cans are used instead as buffers against demand surges in order to reduce holding costs. All inventory decisions are a function of customer demand and production lead times at different stages of the supply chain.

4.4 Integrated Risk Management Model

The integrated risk management model solves for the decision variables (Q_{a0}, Q_{a1}, N_c, N_p, Q_{bj} and Q_{cj}) in order to minimize the expected total opportunity cost E(TOC) along the supply chain that is incurred over the two time spans, T_0 and T_1, while meeting, among others, the constraint related to the value-at-risk of TOC (VaR).

4.4.1 Assumptions

We consider an aggregate demand for beer across multiple brands from which the requirement for aluminum cans is determined. Satisfaction of this demand depends only on the availability of a sufficient quantity of empty cans. We assume that the can supplier has enough capacity to meet any demand from the brewery within a deterministic lead time, and that there is no limitation on the order quantity within the demand distribution defined. We assign a holding cost for stored empty cans that is higher than that of cans undergoing production (P_c). The holding cost of beer at the distribution center is also higher than that of beer undergoing production (P_b). We assume that there is no inventory available from the past at time t_0 and that aluminum sheets inventory can only be replenished during T_0 but not during T_1 due to lead times in producing cans and filling and packaging beer. All inventory flows are assumed to take place as of the beginning of a period and inventory costing is done as of the end of week. The time span T_0 is taken to be 12 weeks and the lead times for empty can and beer production are assumed to be deterministic.

4.4.2 Decisions and Costs in the First Time Span (T_0)

The decision variables in the first time span, T_0, are the quantities of aluminum sheets to order (Q_{a0} and Q_{a1}) and the number of put and call options on aluminum futures to buy (N_p and N_c). The opportunity costs (gains) incurred over this time span are the costs (gains) of initial inventories and the costs (gains) of the call and put options.

4.4.2.1 Cost of Initial Inventories

The opportunity cost associated with initial inventories at time t_0 is given by:

$$Q_{a0}(S_0 - \tilde{S}_1 e^{-rT_0}) + Q_{a0} h_{a0} T_0 e^{-rT_0} \qquad (1)$$

where, r represents the weekly risk-free rate of return and f is an equivalence factor that converts aluminum tons into millions of cans. In (1) and all formulations that follow, h_{i0} and h_{i1} are the weekly costs of carrying a quantity of inventory of type i = {a,b,c}, associated with aluminum sheet quantities purchased at times t_0 and t_1 respectively. The first term in (1) represents the present value of the opportunity cost as described in Section 4.3.3.1. The second term captures the present value of the cost of carrying Q_{a0} over the time span from t_0 to t_1.

The opportunity cost associated with Q_{a1} is given by:

$$Q_{a1}(\widetilde{S}_1 e^{-rT_0} - S_0) \tag{2}$$

This term represents the present value of the opportunity cost (gain) described in Section 4.3.3.1.

4.4.2.2 Cost of Put and Call Options

The cost associated with the purchase of put options is given by:

$$N_p p_0 + N_p p_0 h_{op} T_0 e^{-rT_0} - N_p e^{-rT_0} \mathrm{Max}\{(K - \widetilde{F}_1), 0\} \tag{3}$$

while the cost associated with the purchase of call options is given by:

$$N_c c_0 + N_c c_0 h_{op} T_0 e^{-rT_0} - N_c e^{-rT_0} \mathrm{Max}\{(\widetilde{F}_1 - K), 0\} \tag{4}$$

where, h_{op} is the weekly holding cost associated with put and call options. The first two terms in each of (3) and (4) represent the premium paid for the options and the corresponding holding costs. The third term in (3) and (4) represents the present value of the payoff on the expiration date from the put and call options, respectively.

4.4.3 Decisions and Costs in the Second Time Span (T_1)

Over the time period T_1, can production and beer filling and packing precede the realization of the weekly demands as lead times are involved in these actions. The values of Q_{bj} and Q_{cj} are to be decided before the corresponding weekly demands occur. Following the realization of weekly demand (d_j) at the beginning of each week (w_j) starting from week 6, the quantity to be distributed to the market M_{bj} is set to satisfy demand as much as the beginning inventory allows. The integrated model determines these quantities in order to minimize holding and stockout costs while meeting lead time constraints.

4.4.3.1 Stockout Costs

The present value of the stockout costs over an eight-week beer demand period are given by:

$$\sum_{j=6}^{13} \mathrm{Max}\{(\tilde{d}_j - B_{bj})s, 0\} e^{-r(T_0+t_j)} \qquad (5)$$

This cost is incurred when the beginning inventory in distribution center (B_{bj}) is less than the weekly demand.

4.4.3.2 Holding Costs

The present value of the holding costs associated with the inventory of aluminum sheets are given by:

$$\sum_{j=1}^{13} E_{aj}(u_0 h_{a0} + u_1 h_{a1}) e^{-r(T_0+j)} \qquad (6)$$

The present value of the holding costs associated with the inventory of empty cans are given by:

$$\sum_{j=1}^{8} E_{c(j+L_c)}(u_0 h_{c0} + u_1 h_{c1}) L_c e^{-r(T_0+j)} + \sum_{j=5}^{13} E_{cj}(u_0 h'_{c0} + u_1 h'_{c1}) e^{-r(T_0+j)} \qquad (7)$$

The present value of the holding costs associated with the inventory of canned beer are given by:

$$\sum_{j=5}^{12} E_{b(j+L_b)}(u_0 h_{b0} + u_1 h_{b1}) L_b e^{-r(T_0+j)} + \sum_{j=6}^{13} E_{bj}(u_0 h'_{b0} + u_1 h'_{b1}) e^{-r(T_0+j)} \qquad (8)$$

$$E_{aj} = E_{a8} \text{ for } j = 9, \ldots, 13 \qquad (9)$$

$$E_{c13} = E_{c12} \qquad (10)$$

where, u_0 and u_1 are the proportions of aluminum sheet quantities purchased at time t_0 and t_1, respectively. The unit inventory holding cost has two components, h_{i0} and h_{i1}, that are proportional to the purchase price, S_0 and S_1, respectively. The contribution of each component is then weighted by u_0 and u_1. As units of empty cans and canned beer move downstream, warehousing requirements become more stringent and consequently unit holding costs increase. The model incorporates this increase in holding costs by setting > h_{i0} and > h_{i1}. Equation (6) and the second term in each of (7) and (8) represent the present value of the cost of carrying a surplus quantity of the corresponding inventory type. This surplus is determined by the weekly ending inventory. This approach captures the concept of opportunity cost that is incorporated in our model. The first term in each of equations (7) and (8) represents the present value of the holding cost associated with carrying the surplus quantity during the production phase for the whole lead time period. Equations (9) and (10) ensure that the final ending inventory is carried over to the next planning period.

4.4.4 Objective Function

The objective of our model is to optimize the performance of the supply chain which consists of the can supplier, brewery and distribution center by minimizing the expected total opportunity cost E(TOC) along the supply chain, where the TOC is the summation of equations (1) through (8).

$$\text{Min } E(TOC) \tag{11}$$

4.4.5 Constraints

The following constraints are used in formulating the integrated supply chain risk management model.

$$B_{a1} = Q_a \quad (12)$$

Constraint (12) ensures that the beginning aluminum sheets inventory in the second time period T_1 equals the sum of the quantities of aluminum purchased at time t_0 and t_1.

$$Q_a = Q_{a0} + Q_{a1} \quad (13)$$

$$M_{bj} = \mathrm{Min}(B_{bj}, \tilde{d}_j) \text{ for } j = \{6, \ldots, 13\} \quad (14)$$

Constraint (14) ensures that, as long as there is sufficient inventory at the beginning of each week, all demand is to be satisfied. Having this constraint is important to avoid stockout costs that are rather high compared to holding costs.

$$\mathrm{VaR} \leq v \quad (15)$$

Constraint (15) captures the degree of risk aversion within the supply chain. The value of the upper bound v on the value at risk VAR of the total opportunity cost TOC is a function of the risk management policy to be collectively determined by the supply chain members (can supplier, brewery and distribution center).

$$Q_{a0}, Q_{a1} \leq l_a \quad (16)$$

$$N_p, N_c \leq n \quad (17)$$

$$Q_{bj} \leq l_b \text{ for } j = \{6, \ldots, 13\} \quad (18)$$

$$Q_{cj} \leq l_c \text{ for } j = \{5, \ldots, 12\} \quad (19)$$

Constraints 16 to 19 set upper limits for the decision variables due to operational and financial restrictions.

$$B_{aj} = E_{a(j-1)} \text{ for } j = \{2, \ldots, 8\} \quad (20)$$

$$E_{aj} = B_{aj} - P_{cj} \text{ for } j \in \{1, ..., 8\} \quad (21)$$

$$P_{cj} = Q_{c(j+L_c)} \text{ for } j \in \{1, ..., 8\} \quad (22)$$

$$B_{cj} = E_{c(j-1)} + Q_{cj} \text{ for } j \in \{5, ..., 12\} \quad (23)$$

$$E_{cj} = B_{cj} - P_{bj} \text{ for } j \in \{5, ..., 12\} \quad (24)$$

$$P_{bj} = Q_{b(j+L_b)} \text{ for } j \in \{5, ..., 12\} \quad (25)$$

$$B_{bj} = E_{b(j-1)} + Q_{bj} \text{ for } j \in \{6, ..., 13\} \quad (26)$$

$$E_{bj} = B_{bj} - M_{bj} \text{ for } j \in \{6, ..., 13\} \quad (27)$$

Constraints (20), (23) and (26) ensure the transfer of inventories remaining at the end of one week to the next week. Constraints (21, 22), (24, 25), and (27) ensure the inventory flow conservation every week for the inventories of aluminum sheets, empty cans and beer, respectively.

4.5 Sequential Model

The integrated model represents a centralized decision approach based on which operational and financial hedging decisions are made simultaneously. This approach is not widely used by firms. Instead, different functional areas make operational hedging decisions and financial hedging decisions independently. We represent this latter approach with a sequential model that consists of two sub-models: i) the operational hedging sub-model and ii) the financial hedging sub-model. The operational sub-model is a replicate version of the integrated model with the exclusion of the financial variables and costs. Using the same problem parameters and probabilistic inputs used in the integrated model, the operational sub-model solves for all the decision variables in the integrated model excluding the number of put and call options N_p and N_c. The optimal values of the decision variables obtained in the operational sub-model are then entered as fixed parameters in the financial hedging sub-model that solves for N_p and N_c to minimize the expected total opportunity cost. The optimal values of the decision variables associated with the sequential model are the values optimized by the operational sub-model and then by the financial hedging sub-model. Hence, it is important to note that for the experimental design and statistical analyses that follow, the performance of the sequential model is measured by the expected total opportunity cost obtained by the financial hedging sub-model.

4.6 Experimental Design

4.6.1 Factorial Design

In order to study the performance of our integrated model under various operating environments and to compare the integrated model to the sequential model we conducted factorial experiments. The three models are run on the same problem parameters controlling for the values of the three major factors: i) the VAR of total opportunity cost ii) demand variability and iii) volatility of aluminum price. The upper bound v on the VAR of total opportunity cost in equation (15) is a managerial decision variable related to the supply chain stakeholders' risk management policy. The level of the upper bound is implicitly defined by the degree of risk aversion of the supply chain with higher levels corresponding to lower levels of risk aversion. The base value of v of $1.8 million is selected after a large number of trial runs were performed. Even though the level of v is a managerial decision, the values tested in the trial runs are limited by two boundaries. When v is very high, the variation of TOC is found to be high which makes the statistical analyses problematic. When v is very low, a feasible solution cannot be obtained due to the tight constraint limit. The second factor, the variability of the demand for beer, represents the uncertainty emanating from the supply chain's downstream. We quantify this uncertainty by the standard deviation of weekly beer demand (SDD). The base level of SDD of 4.5 million cans corresponds to a figure obtained in private communication with a major brewery. The third factor, aluminum price volatility (APV), is a source of uncertainty encountered at the supply chain's upstream. This volatility is captured by the annualized standard deviation of return on both the aluminum spot and aluminum futures, σ_1 and σ_2, that are used to estimate the spot and futures price, respectively, in equations (28) and (29), in Appendix A.1, which explains the process used to simulate aluminum spot and futures prices. We considered three levels of APV, each level being represented by a value of σ_1 and a value of σ_2. The values of σ_1 of 25.9% and σ_2 of 23.9% which were estimated from historical data according to the procedure explained in Appendix A.1, are considered as 'base' values.

Table 4.1 provides the base values of the three factors as well as the low (L) and high (H) values used in the experimental design. The lower and upper levels of the three factors were selected based on observations made during a large number of trial runs at the model development stage. The deviations from the base level are in percentage terms and the range of 15 – 16.7% are consistent for the three factors.

Table 4.1 Descriptions of experimental design factors

Factor	Designation	Code	Level			Units
			L	B	H	
Value-at-risk	VAR	A	1.5	1.8	2.1	Million $
Demand uncertainty	SDD	B	3.8	4.5	5.2	Million cans
Aluminum price volatility*	APV	C	(21.3 , 20.3)	(25.0 , 23.9)	(28.8 , 27.4)	%

* APV levels are represented by pairs of values of σ_1 and σ_2 (σ_1,σ_2)

The three factors are incorporated in each model as follows: i) VAR is the value of the upper limit (v) in constraint (15); ii) SDD is a parameter defining, along with the mean, the distribution function of the weekly demand (d_j) that is simulated according to the procedure explained in Appendix A.2; iii) APV is incorporated through σ_1 and σ_2 that are used to simulate S_1 and F_1, respectively, as explained in Appendix A.1.

4.6.2 Simulation Environment

Using three levels for each of the three factors, we identify 27 treatment combinations (i.e. 3^3) for each of the three models (operational, financial and integrated) for a total of 81 model versions. To compare the effects of the various treatment combinations, we determine for each of the 81 model versions the minimum expected total opportunity cost, E(TOC). This cost is the response variable that we use to compare the effects of treatment combinations. We use a simulation-based optimization tool provided by @RISK, which is part of the Decision Tools Suite provided by Palisade, to determine the values of the decision variables that minimize E(TOC) under the relevant constraints. Starting with initial values of the decision variables, the optimization involves running a large number of simulations. Each simulation consists of 10,000 iterations. For each iteration, random values of the probabilistic inputs (S_1, F_1, and d_j) are generated and used in the calculation of the expected total opportunity cost. The software uses genetic algorithms to find new solutions that improve the value of the objective function. Using the optimal solution found for the decision variables, we run eight simulations as replications on each of the 81 model versions and record the values of E(TOC). These values then represent the response variable in eight replications for each treatment combination in the experimental design.

4.6.3 Values of Major Parameters

The values used for the parameters in 81 model versions are summarized in Table 4.2.

Table 4.2 Values used for the parameters

Parameter	*Value*	*Source/Justification*
S_0	\$2,287	London Metal Exchange (LME), spot price of aluminum on March 31, 2010
F_0	\$2,319	LME, closest to maturity futures price of aluminum on March 31, 2010
$c_0 = p_0$	\$105	Calculated using the Black model (Hull (2006), pp. 332-333))
K	\$2,319	Exercise price of at-the-money options
T_0	12 weeks	Assumed to capture significant fluctuations in aluminum spot and futures prices
f	13.38 Kg/1,000 cans	Data provided by a major brewery
r	10%	Assumed (Shanker and Balakrishnan (2008))
h	18%	Estimated
h'	36%	Holding cost marked up to capture special logistics requirements
n	4,000 tons	Based on assumed financial constraint
q_a	4,000 tons	Based on assumed operational constraint
q_b	30 million cans	Based on operational constraint
q_c	60 million cans	Based on operational constraint

We used the data published by the LME for the dates from January 6 to March 30, 2010 to estimate standard deviations on aluminum spot and futures prices. As the options are purchased at t_0 and have maturity dates at t_1, the number of trading days considered in the simulations of S_1 and F_1 and in pricing the options is 60 trading days. The option prices are determined using Black's model as described in Hull (2006; pp 332-333). Considering the exploratory nature of our study, we incorporated a 12 week period between t_0 and t_1 to capture any significant fluctuations in aluminum spot and futures prices. Following Shanker and Balakrishnan (2008) and Ritchken and Tapiero (1986), a risk free rate of 10% was assumed. The value of the stockout cost used in our model is obtained through private communications with a major brewery.

4.7 Findings, Managerial Insights and Statistical Analyses

In the following sections, we refer to the solutions obtained as the 'optimal solutions' since these are found by the optimization procedure using the genetic algorithms imbedded in @RISK software. However, as in any stochastic programming model, we optimize the expected value of the objective function. Random values of the probabilistic input with continuous distributions are generated using simulation. We believe that the obtained solutions are close to optimal.

4.7.1 Findings

Table 4.3 depicts the main optimization results of each model version. For easy reference, each model version representing a treatment combination is designated by letters O, S and I referring to the operational hedging sub-model, the financial hedging sub-model (hence, the sequential model) and the integrated model. For example, I10 is the integrated model in which VAR = 1.8 million dollars, SDD = 3.8 million cans and APV = Low (21.3%, 20.3%). For the statistical analyses and managerial insights to follow, we present in Table 4.3 the optimal solutions in terms of only four decision variables (Q_{a0}, Q_{a1}, N_p and N_c) and the optimal value of E(TOC) and its standard deviation (Dev). @RISK fits a distribution to the values of TOC obtained for each of 10,000 iterations in a simulation run. This distribution has a mean of E(TOC) and a standard deviation. In Table 4.3, E(TOC) and Dev are the means of their corresponding values in the eight replications of each treatment.

Table 4.3 Optimization results for the experimental design

Factor Level			Sequential Model										Integrated Model						
			Operational Sub-model					Financial Hedging Sub-model											
VAR	SDD	APV		E(TOC)	Dev	Q_{a0}	Q_{a1}		E(TOC)	Dev	N_p	N_c		E(TOC)	Dev	Q_{a0}	Q_{a1}	N_p	N_c
1.5	3.8	L	O01	608.0	571.3	47.8	124.0	S01	596.9	716.1	2,322	734	I01	579.7	841.4	40.2	133.1	3,664	980
		B	O02	610.4	580.5	46.3	127.2	S02	599.0	810.4	2,915	953	I02	591.8	789.5	40.3	133.1	2,504	987
		H	O03	619.0	596.9	48.1	125.5	S03	612.8	803.1	2,513	1,033	I03	622.9	731.4	37.6	136.4	1,607	1,068
	4.5	L	O04	785.3	567.0	68.6	109.4	S04	784.5	609.3	644	238	I04	737.1	733.4	52.0	125.6	2,373	872
		B	O05	786.6	569.6	68.7	109.4	S05	783.6	652.3	1,420	573	I05	755.9	669.0	53.6	124.3	1,293	1,268
		H	O06	788.4	579.1	69.1	109.6	S06	790.2	649.2	1,134	538	I06	758.7	676.1	58.5	119.1	1,056	710
	5.2	L	O07	945.8	587.4	81.2	101.3	S07	944.2	628.6	954	630	I07	893.5	635.8	58.1	125.4	379	900
		B	O08	957.2	575.9	82.3	101.2	S08	958.2	618.9	652	416	I08	909.5	626.7	58.9	125.2	310	1,344
		H	O09	958.1	573.3	82.4	101.3	S09	960.6	616.2	516	335	I09	913.2	624.6	62.2	122.0	397	1,119
1.8	3.8	L	O10	556.1	617.0	31.6	141.5	S10	522.6	983.0	4,000	0	I10	490.3	1,041.6	12.2	161.5	4,000	379
		B	O11	566.1	666.6	24.1	149.5	S11	545.6	1,074.1	4,000	711	I11	521.9	1,081.0	18.7	155.9	3,942	834
		H	O12	597.2	639.9	41.2	132.4	S12	575.1	1,064.3	3,830	641	I12	530.0	1,127.9	17.6	156.0	3,986	1,949
	4.5	L	O13	665.9	713.9	32.4	145.0	S13	645.7	980.1	4,000	1,255	I13	628.3	982.1	18.2	157.9	3,415	1,158
		B	O14	695.8	694.9	39.4	136.8	S14	677.6	1,006.5	3,687	870	I14	647.2	999.8	19.0	158.8	3,106	1,430
		H	O15	725.1	696.7	50.8	124.5	S15	723.2	805.8	1,413	538	I15	658.3	827.3	18.6	158.7	579	964
	5.2	L	O16	875.8	693.5	66.2	113.6	S16	873.4	734.5	803	408	I16	835.9	933.2	56.8	125.4	4,000	837
		B	O17	900.0	664.0	73.6	106.4	S17	895.9	738.5	1,022	144	I17	848.2	792.3	56.2	123.0	1,423	856
		H	O18	908.1	671.5	74.1	106.9	S18	898.5	807.3	1,963	370	I18	853.6	800.2	56.5	123.1	1,344	1,014
2.1	3.8	L	O19	531.7	662.4	13.2	162.1	S19	496.0	1,059.7	4,000	0	I19	483.9	1,076.2	11.7	161.6	4,000	0
		B	O20	544.5	726.8	18.6	162.2	S20	510.7	1,192.5	4,000	3	I20	500.6	1,178.2	17.7	155.5	4,000	0
		H	O21	583.6	655.2	38.0	134.8	S21	553.1	1,168.8	4,000	0	I21	510.5	1,259.7	17.5	156.0	4,000	453
	4.5	L	O22	625.7	798.3	15.8	170.3	S22	592.4	1,141.7	4,000	297	I22	572.3	1,156.2	7.0	168.9	4,000	253
		B	O23	631.6	824.8	17.8	157.1	S23	607.6	1,136.8	3,381	527	I23	599.0	1,210.9	8.2	169.4	4,000	912
		H	O24	662.2	852.2	27.3	158.3	S24	647.6	1,183.2	3,564	1,217	I24	610.6	1,269.1	7.8	169.1	4,000	1,811
	5.2	L	O25	729.1	871.6	14.4	163.7	S25	710.4	1,051.5	2,717	638	I25	741.0	924.2	8.1	169.4	1,156	2,305
		B	O26	765.4	856.4	28.2	149.8	S26	760.1	1,013.6	2,185	690	I26	756.8	888.4	8.2	169.7	37	2,854
		H	O27	807.2	843.4	40.8	137.6	S27	801.5	1,024.4	2,590	1,150	I27	786.6	1,152.6	42.0	136.9	3,749	870

E(TOC): Expected total opportunity cost (in thousands of dollars); Dev: Standard deviation of TOC (in thousands of dollars)
Q_{a0}: Quantity of aluminum purchased at time t_0 (in million cans); Q_{a1}: Quantity of aluminum purchased at time t_1 (in million cans)
Np: Number of put options; Nc: number of call options

Table 4.3 reveals that E(TOC) obtained for each of the three models satisfies the following three intuitive patterns:

- For the same demand standard deviation and the same aluminum price volatility: when VAR increases, E(TOC) decreases (e.g.: $E(TOC)_{I19} > E(TOC)_{I10} > E(TOC)_{I01}$)
- For the same VAR and the same aluminum price volatility: when demand standard deviation increases, E(TOC) increases (e.g. $E(TOC)_{I07} < E(TOC)_{I04} < E(TOC)_{I01}$)
- For the same VAR and the same demand standard deviation: when aluminum price volatility increases, E(TOC) increases (e.g. $E(TOC)_{I03} < E(TOC)_{I02} < E(TOC)_{I01}$)

4.7.2 Comparison of Integrated and Sequential Models and Managerial Insights

In this section, we present the results from Table 4.3 in two-way Tables 4.4 to 4.6 for easy comparisons. In these tables, rows correspond to SDD levels and columns correspond to VAR levels. Each cell represents a range corresponding to the three levels of APV. As APV exhibits daily fluctuations while SDD and VAR are more stable (SDD has weekly variation and VAR represents a managerial decision), presenting the results in this manner makes it easier to draw managerial insights.

4.7.2.1 Overall Superiority of the Integrated Model over the Sequential Model

Table 4.3 reveals that the integrated model performs better than the sequential model in all the cases, except for cases 3 and 25. In these two cases, the difference between the two expected opportunity costs is not statistically significant. The superiority of the integrated model over the sequential model is measured by the percentage difference between the corresponding expected total opportunity costs, as given by: ($E(TOC)_{\text{financial hedging}}$ -

$E(TOC)_{integrated}$) / $E(TOC)_{integrated}$) x 100. This percentage difference is presented in Table 4.4.

Table 4.4 E(TOC) percentage difference between integrated and sequential models

	VAR		
SDD	1.5	1.8	2.1
3.8	0.9 – 3.0%	4.0 – 8.4%*	1.4 – 8.5%*
4.5	3.4 – 6.3%*	2.7 – 10%*	2.2 – 7.2%*
5.2	5.2 – 5.7%*	4.5 – 5.8%*	0 – 1.7%

* Statistically significant at 0.05 significance level

Managerial Insights: In the context of our experiment, a less risk averse supply chain chooses to be exposed to a VAR that is higher than that accepted by a more risk averse supply chain in order to achieve a lower expected total opportunity cost. Improvement in E(TOC) when VAR is 2.1 is statistically significant in only two cases of the possible nine, (SDD = 3.8, APV = H) and (SDD = 4.5, APV = H). Hence, a less risk averse supply chain may not find it compelling to integrate the operational and financial hedging decisions except for those situations in which the aluminum price volatility is high while the demand variability is low to medium. However, for a more risk averse supply chain (willing to accept VAR at 1.5 and 1.8 levels), the integrated model results in significantly lower opportunity costs in most of the cases studied.

4.7.2.2 Operational and Financial Hedging

In this section, we discuss the operational and financial hedging strategies incorporated in the integrated and sequential models. While financial hedging is executed through purchasing put and call options, operational hedging against aluminum price increase can be viewed by the ratio (u_0) of the quantity of aluminum sheets purchased at t_0 to the total quantity purchased at t_0 and t_1.

Operational Hedging: A supply chain using the sequential model buys at time t_0 a proportion of its total aluminum quantity that is larger than that purchased by a supply chain using the integrated model. Table 4.5 depicts ranges of u_0 in the two models. A range encompasses values of u_0 at the three levels of APV at each (VAR / SDD) combination.

Table 4.5 Ratio (u_0) of aluminum sheets purchased at t_0 to total purchased quantity

	VAR					
	1.5		1.8		2.1	
SDD	Integrated	Sequential	Integrated	Sequential	Integrated	Sequential
3.8	22 – 23%	27 – 28%	7 – 11%	14 – 24%	7 – 10%	8 – 22%
4.5	29 – 33%	39%	10 – 11%	18 – 29%	4 – 5%	8 – 15%
5.2	32 – 34%	44 – 45%	31%	37 – 41%	5 – 23%	8 – 25%

As both inventory and financial decisions are made simultaneously in the integrated model, the supply chain is hedged against a possible increase in aluminum prices by the purchase of a quantity Q_{a0} of aluminum sheets and of call options. In the absence of the latter hedging instrument in the operational sub-model, only Q_{a0} can hedge against an aluminum price increase which explains the higher ratio in all cases. The following patterns can be observed in both models:

- For the same SDD: as VAR increases, u_0 decreases, indicating supply chain's willingness to wait (and take chances) to buy a higher quantity of aluminum at t_1.
- For VAR values of 1.5 and 1.8, for a given VAR: as SDD increases, u_0 increases, pointing to a cautious behavior in terms of buying higher quantities of aluminum earlier at t_0.

Financial Hedging: Table 4.3 depicts the difference in the financial strategies adopted in the integrated and the sequential models. In the latter model, as financial hedging decisions are made after inventory levels are determined, we observe the contribution of financial hedging decisions in further reducing the E(TOC) optimized by the operational sub-model. This contribution is measured by the percentage difference between the corresponding costs, as given by ($E(TOC)_{operational}$ - $E(TOC)_{financial\ hedging}$/) $E(TOC)_{operational}$) x 100 and is presented in Table 4.6.

Table 4.6 E(TOC) percentage difference between operational and financial hedging sub-models

	VAR		
SDD	1.5	1.8	2.1
3.8	1.1 – 2.1%	3.8 – 6.4%*	5.5 – 6.7%*
4.5	0.3 – 0.6%	0.6 – 3.1%*	2 – 5.1%*
5.2	0%	0.2 – 1.2%	0.7 – 2.3%

* Statistically significant at 0.05 significance level

The results depicted in Tables 4.5 and 4.6 reveal a negative relationship between the effects of financial hedging on E(TOC) in the sequential model and the degree of operational hedging (u_0). At VAR = 1.5, u_0 is the highest and financial hedging has no significant effect. At VAR = 1.8 and 2.1, the effects are most significant when SDD = 3.8 in which case u_0 is the lowest. When SDD = 4.5, financial hedging has a significant effect only when aluminum price volatility is low, in which case u_0 is the lowest.

Managerial Insights: Whether integrated or individual hedging models are used, a less risk averse supply chain hedges aluminum price risk with much less physical quantity of aluminum than does a more risk averse supply chain which would procure up to 45% of the total quantity at time t_0. The latter tends to use more operational hedging as demand variability increases. A highly risk averse supply chain that hedges with higher levels of inventory would not further hedge in a significant manner with financial instruments. A less risk averse supply chain, on the other hand, does hedge further using financial instruments, especially when demand variability is low.

4.7.3 Statistical Analyses

As the main objective of our research is to study the benefits of integrating operational and financial hedging decisions, we perform statistical analyses on the integrated model and the sequential model in order to explain their performances under varying levels of the three experimental design factors and to draw further managerial insights. Assessing the performance of the operational hedging sub-model by itself does not serve our research objective. However, its contribution to the sequential model is relevant for analysis. The functioning of the operational sub-model is incorporated in the sequential model by setting the values of the decision variables obtained from the former as input parameters for the latter.

We use Design Expert® software to perform factorial analysis on the data generated from the optimization runs. The software generates a quadratic regression model that explains the variations in the response variable, E(TOC), for each of the integrated model and the sequential model. The quadratic regression model includes terms representing the three factors (VAR, SDD, APV) in addition to interaction terms. The regression model can be used to predict the value of the response variable for any combination of the factors within their corresponding lower and upper levels. We will refer to the quadratic model as the regression model to avoid confusion with the original hedging models used for optimization. Thus, in the following discussion, the regression integrated model is the model we use to predict E(TOC) that can be optimized by the integrated model. The same applies for the sequential model. We also used Design Expert® on the aggregated data obtained from the integrated and sequential models. For the analysis of this aggregated data, we introduced a fourth factor. This factor is categorical with two levels representing the source of the data: integrated model and sequential model. An aggregate quadratic regression model is generated in this respect to explain the variation of E(TOC) within and between the integrated and sequential models.

4.7.3.1 Regression Models

For each of the three regression models the software runs an ANOVA to test for the overall model fit and for the significance of the effects of each term in the model on the response variable. Table 4.7 presents part of the ANOVA results for the aggregate regression model. In addition to the main effects of the factors, the interaction between factors have significant effects on E(TOC). We discuss these interactions and provide managerial insights in the following sub-section.

Table 4.7 ANOVA results for aggregate regression model

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	6.51E+12	52	1.25E+11	7,686	< 0.0001
A-VAR	1.66E+11	1	1.66E+11	10,165	< 0.0001
B-SDD	6.84E+11	1	6.84E+11	41,983	< 0.0001
C-APV	1.79E+10	1	1.79E+10	1,098	< 0.0001
D-Model	2.12E+10	1	2.12E+10	1,304	< 0.0001
AB	2.24E+10	1	2.24E+10	1,374	< 0.0001
AC	3.18E+09	1	3.18E+09	195	< 0.0001
AD	6.16E+08	1	6.16E+08	38	< 0.0001
BC	2.16E+09	1	2.16E+09	133	< 0.0001
BD	9.51E+08	1	9.51E+08	58	< 0.0001
CD	3.40E+09	1	3.40E+09	208	< 0.0001
ABC	2.24E+09	1	2.24E+09	137	< 0.0001
ABD	1.66E+09	1	1.66E+09	102	< 0.0001
ACD	7.88E+08	1	7.88E+08	48	< 0.0001

A number of diagnostic tests are performed to detect any abnormality in the models. These tests are: i) normal probability plot of Studentized residuals to check for normality of residuals, ii) Studentized residuals versus predicted values to test for assumption of constant variance, iii) externally Studentized residuals to look for outliers and iv) Box-Cox plot for power transformations. All the three regression models passed the diagnostic tests. Figure 4.2 illustrates the test plots for the aggregate regression model.

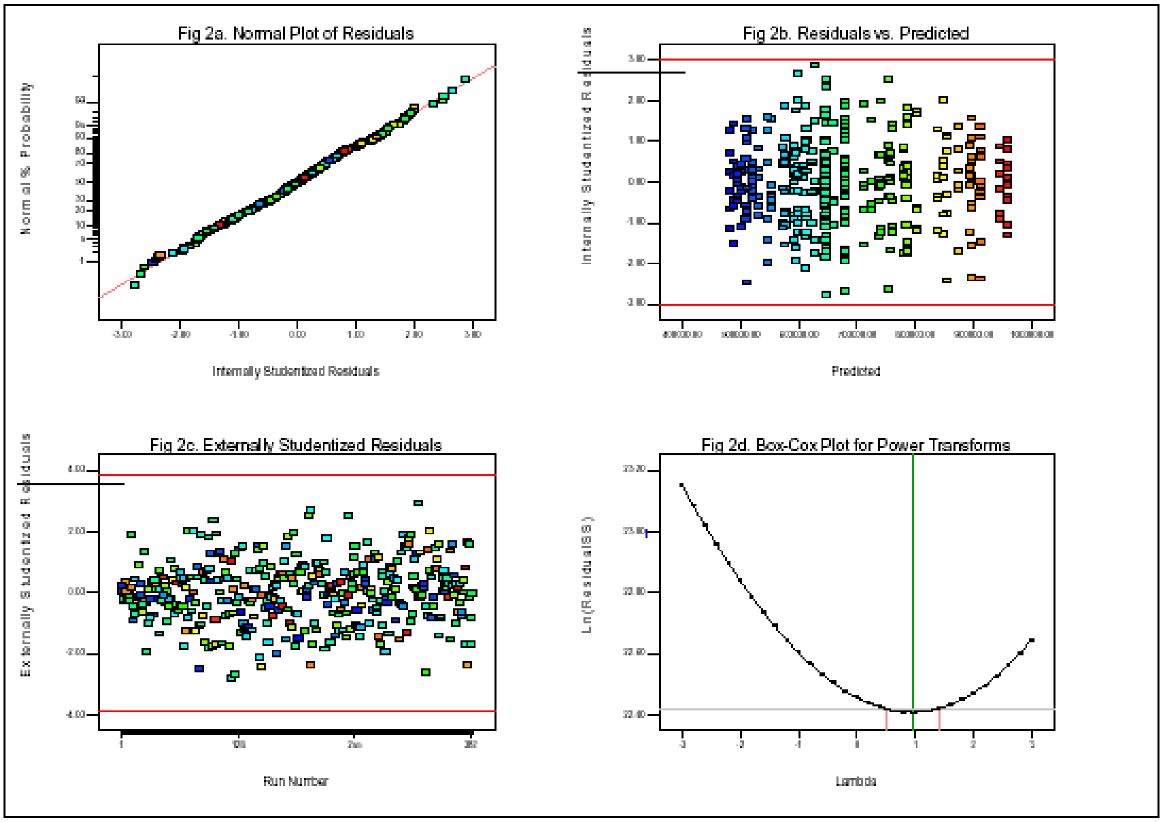

Figure 4.2 Test plots for the aggregate quadratic regression model

4.7.3.2 Main and Interaction Effects

As illustrated in Table 4.7, all the factors, as well as their interactions, have significant effects on E(TOC). Figures 4.3 to 4.5 illustrate the main effects of the factors and their interaction effects. The bars at the end points of the graphs represent the least significant differences of the average values of the opportunity cost, corresponding to 95% confidence level. Each figure depicts the change in E(TOC) for both the integrated and sequential models as a function of one factor at four combinations of the other two factors (at their lowest and highest levels). We will now highlight some of these effects and draw managerial insights accordingly.

The main effects of the three factors of VAR, SDD and APV on E(TOC) are visually evident in Figures 4.3 - 4.5. As noted in Section 4.7.1, there is a negative relationship between VAR and E(TOC) and a positive relationship between each of SDD and APV with E(TOC). However, the degree of impact of the three factors on E(TOC) vary between the integrated and sequential models. In Fig. 4.3c, for example, the marginal decline in E(TOC) as VAR increases is much lower in the sequential model than in the integrated model. On the other hand, while E(TOC) exhibits a continuous decline as VAR increases in the sequential model, the change is minimal in the integrated model once VAR reaches the level of 1.9.

While in most of the cases the integrated model results in a lower E(TOC) compared to that of the sequential model, some exceptions can be observed nevertheless. Fig. 4.3b and 4.3c reveal cases where E(TOC) of the integrated model is higher than that of the sequential model. This occurs when VAR is above 2 in the former figure and below 1.54 in the latter. Similar observations can be made in Fig. 4.4b when SDD is higher than 4.9 and in Fig. 4.4c when SDD is below 3.94. Fig. 4.5a and 4.5d also reveal that the sequential model outperforms the integrated model when APV is higher than 26.4% and lower than 24.7%, respectively. However, we find no statistical significance in the difference between the expected opportunity costs of the integrated and sequential models in these cases.

Managerial Insights: i) In general, a less risk averse (LRA) supply chain (willing to accept high VaR of total opportunity cost) can be at a substantial advantage with respect to a more risk averse (MRA) supply chain. ii) The LRA supply chain performs best when it operates under low demand variability and low aluminum price volatility. iii) The supply chain would not always be able to exploit the benefits of integrating operational and financial decisions. Under certain business environments, such as described above, the integrated model may not significantly outperform the sequential model.

While results in Table 4.3 show positive and negative relationships between each factor and E(TOC), Figures 4.3 to 4.5 provide visual insights about these relationships. Figure 4.3 exhibits clear changes in the response of E(TOC) to variations in VAR under the different combinations of SDD and APV. This is true for both the integrated and sequential models. For example, E(TOC) line changes from a concave to a convex curvature when SDD changes from 3.8 in Fig. 4.3a. to 5.2 in Fig. 4.3b. In the integrated model, when SDD is low, E(TOC) does not improve in the cases when VAR becomes higher than 1.9 million dollars. On the other hand, when SDD is high, E(TOC) continues declining as VAR increases and it reaches a minimum value at VAR = 2.1 million dollars. Similarly, Figure 4.5 exhibits clear changes in the response of E(TOC) to variations in APV under the different combinations of SDD and VAR. For example, the line of E(TOC) in the integrated model changes from curvilinear in Fig. 4.5c to linear with a mild slope in Fig. 4.5d.

Managerial Insights: i) In contrast with the general relationship observed between VAR and E(TOC), in the case of low demand variability, the supply chain would find it unnecessary to accept higher risks (in terms of high VAR) as the marginal savings are not significant (as exhibited in flattening curvature at the right tail of E(TOC) in Fig. 4.3a and 4.3c). ii) Under low demand variability and using the integrated model, a MRA supply chain benefits from decline in aluminum price volatility much more than LRA supply chain. On the other hand, when demand variability is high, a LRA supply chain benefits from decline in aluminum price volatility much more than HRA supply chain.

The quadratic regression model allows the prediction of E(TOC) for any factor level within the range defined. As examples, Figure 4.6 and Figure 4.7 depict a 3-dimenional response surface that is a function of VAR and SDD for the integrated model and the sequential model, respectively, where the APV level is fixed at its base value. Design Expert® experimental design software allows the user to visualize the change in the response surface while changing the APV level on the sliding scale provided. As one changes the APV level in small increments on the sliding scale, the surface in Figure 4.6 for the integrated model is observed to shift slightly up or down while the contour of the response surface remains almost identical during these shifts (not shown here). In contrast, when the same what-if analysis is done for the sequential model in Figure 4.7, not only the vertical shifts are more pronounced than those for the integrated model for the same APV change, but one also observes distortions in the contour of the surface given in Figure 4.7 (not shown here). This observation was repeated to a large extent when the factors on the graph and the third factor on the sliding scale were switched. This clearly suggests that the performance of the integrated model is more robust compared to that of the sequential model when subjected to variations in business conditions associated with the three experimental design factors used.

4.8 Concluding remarks

The SCRM integrated model developed captures the supply chain risk management process that requires the collaboration of supply chain members (aluminum can supplier, brewery and distributor) as well as the collaboration of functional units (operations and finance) of these members. The model integrates operational and financial hedging decisions to minimize the expected total opportunity cost of a beer supply chain exposed to uncertainties from upstream (commodity price fluctuations) and downstream (demand variability). Our findings reveal that the cost performance of the integrated model is not only superior to that of the sequential model where hedging decisions are made independently by functional units, but also more robust when subjected to changing business environment. The findings also shed light on the business environment in which the integrated model significantly performs better. For example, a less risk averse supply chain can be at a substantial advantage with respect to a highly risk averse supply chain when it operates under low demand variability and low aluminum price volatility. For more risk averse supply chains, the integrated model proves to be more compelling as the decrease in total opportunity cost, compared to the sequential model, is significant. A less risk averse supply chain, however, can still exploit the integrated model by reducing its expected total opportunity cost for cases in which the aluminum price volatility is high. The type of hedging strategy used against input commodity price increase depends also on the risk aversion level and the demand variability. In general, the supply chain studied has hedged more with operational and less with financial instruments when faced with higher demand variability. However, as the supply chain becomes less risk averse, it tends to hedge less with operational and more with financial instruments.

The SCRM integrated model developed can be extended and enriched in a number of different operational and financial hedging directions. As possible model extensions, multiple commodities (e.g. aluminum and barley) and multiple suppliers (of aluminum cans and barley) can be incorporated into the model. The model can further be enriched through considering variable lead times (for empty can production and beer filling) and incorporating foreign currency exchange rate fluctuations (when purchasing aluminum and barley from global markets).

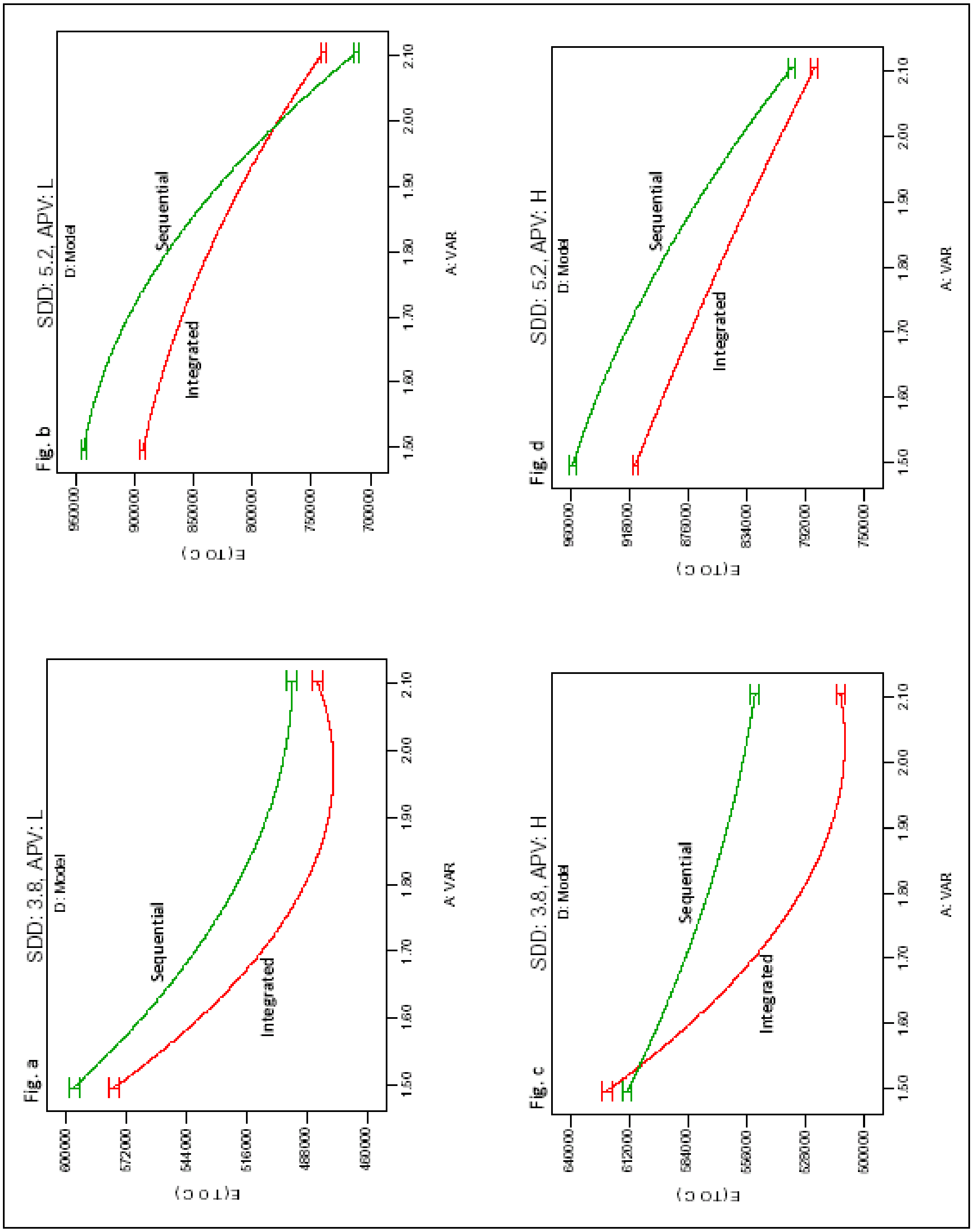

Figure 4.3 Effects of VAR on E(TOC) at lowest and highest levels of SDD and APV

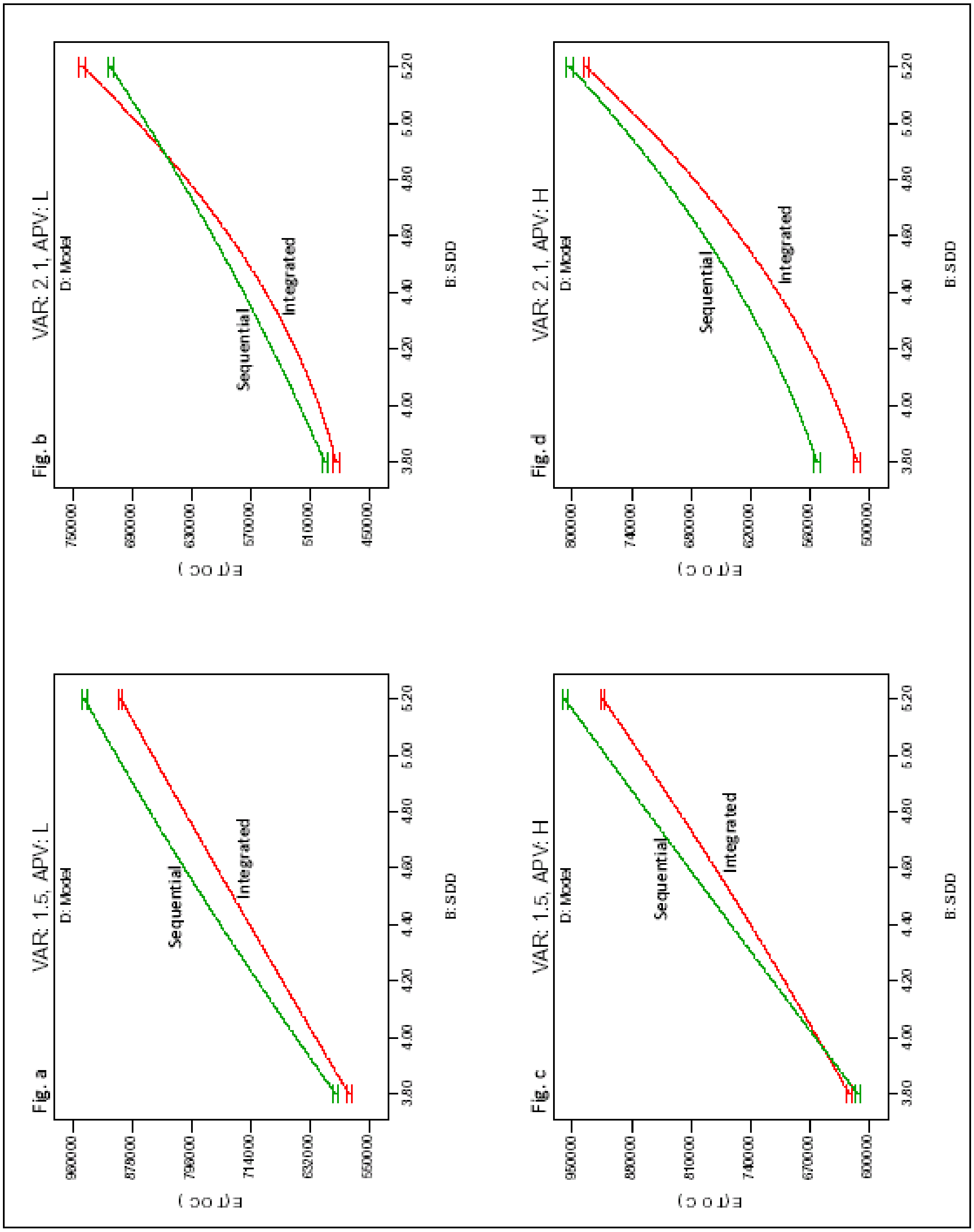

Figure 4.4 Effects of SDD on E(TOC) at lowest and highest levels of VAR and APV

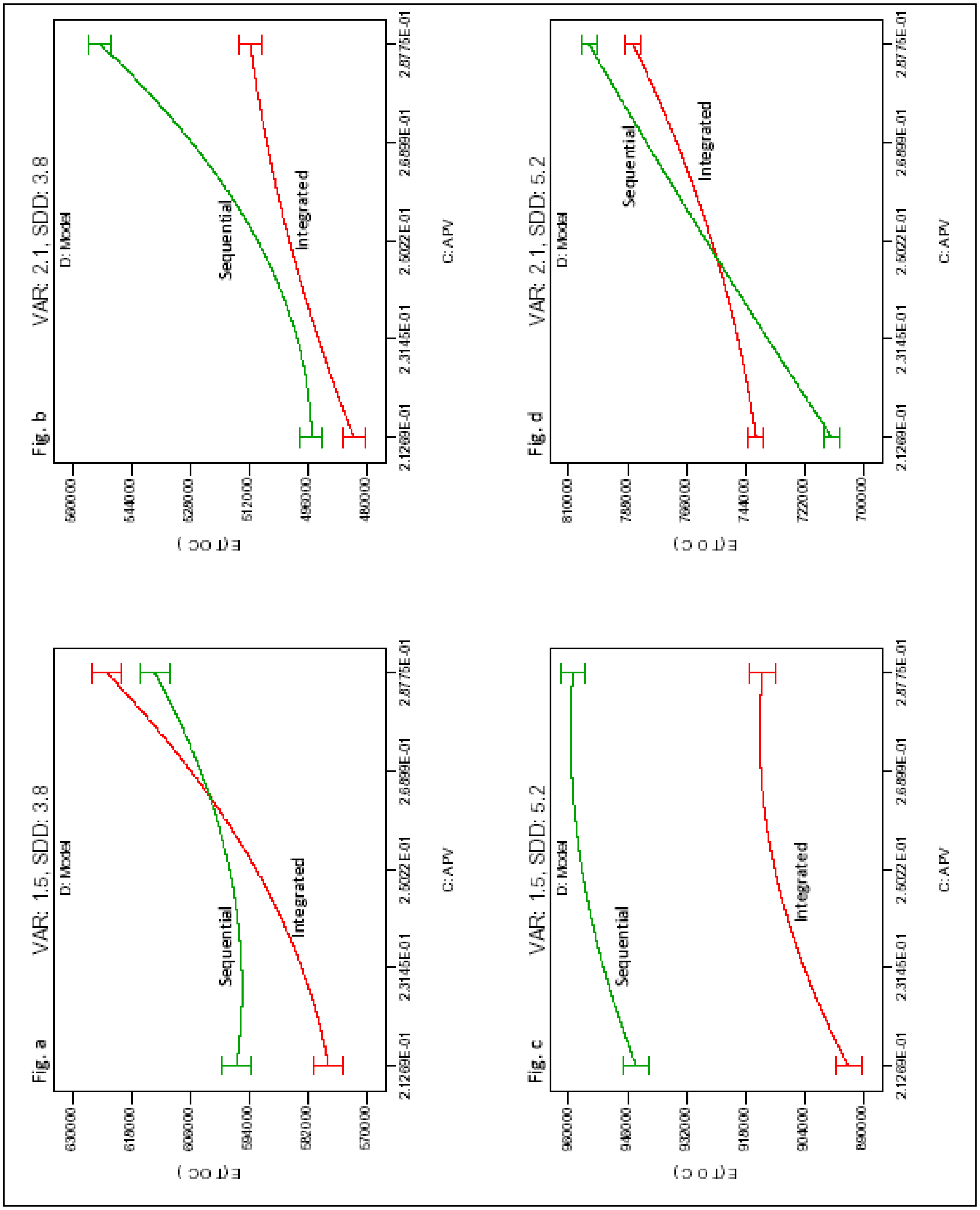

Figure 4.5 Effects of APV on E(TOC) at lowest and highest levels of VAR and SDD

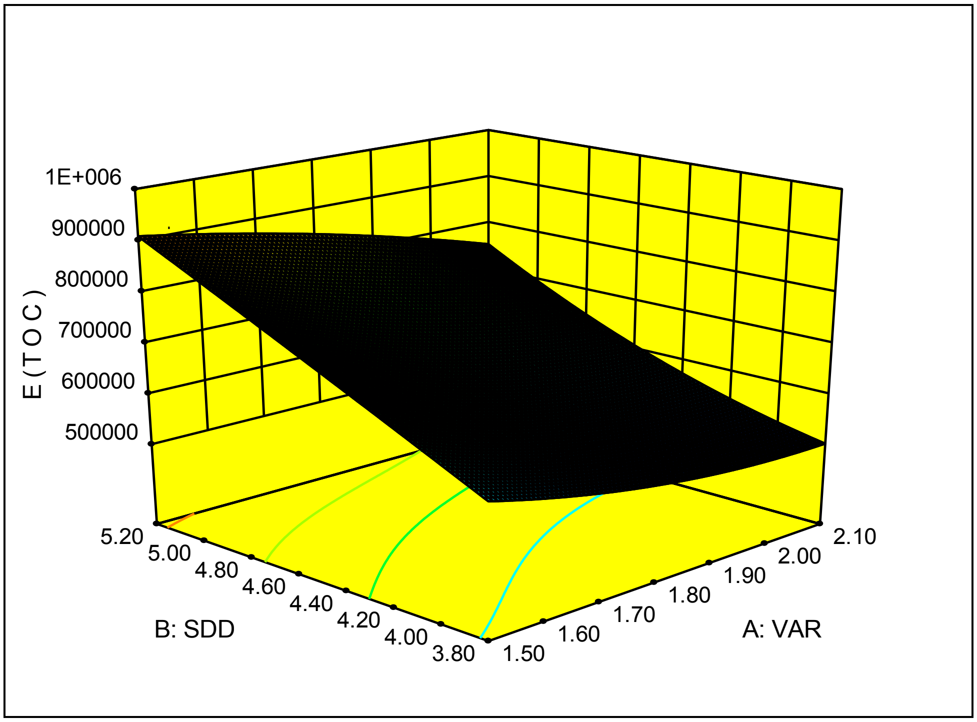

Figure 4.6 3D response surface (Model: integrated, APV: B)

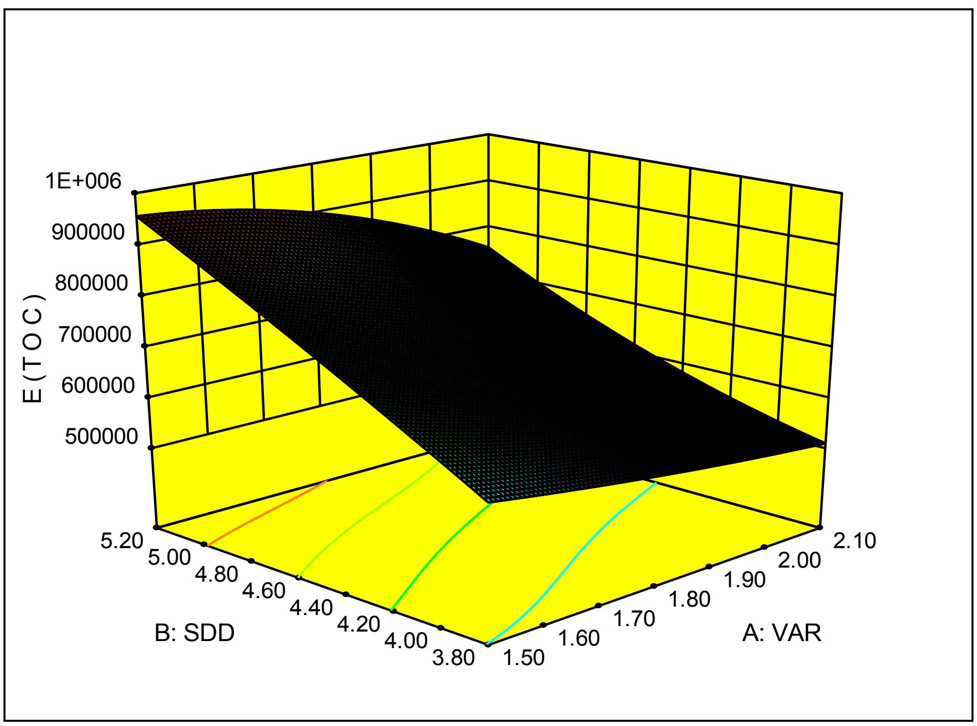

Figure 4.7 3D response surface (Model: sequential, APV: B)

Appendix A - Simulating the Probabilistic Input

A.1. Aluminum Spot and Futures Prices

Assuming that aluminum spot and futures prices are lognormal distributed, we simulate these prices at the future time t_1, which coincides with the options' expiration date, according to the procedure presented in Hull (2006). Thus,

$$S_1 = S_0 \times \exp\left[\left(\mu_1 - \frac{\sigma_1^2}{2}\right)T + \sigma_1\sqrt{T}\varepsilon_1\right] \qquad (28) \qquad \text{and}$$

$$F_1 = F_0 \times \exp\left[\left(\mu_2 - \frac{\sigma_2^2}{2}\right)T + \sigma_2\sqrt{T}\varepsilon_2\right] \qquad (29)$$

where S_0 and F_0 are spot and futures prices, respectively, at the current time t_0; μ_1 and μ_2 are the annualized mean of the continuously compounded returns on the spot and on the futures, respectively; σ_1 and σ_2 are the annualized standard deviations of the continuously compounded returns on the spot and on the futures, respectively; μ_1, μ_2, σ_1 and σ_2 are estimated using historical daily data on spot and futures prices obtained from Bloomberg for a 12 week period in which the last date coincides with the date just prior to the options' purchase date. T is the time (in years) to the options' expiration dates. ε_1 and ε_2 represent standard normal random variables whose correlation is ρ_{12} which is the coefficient of correlation between the returns on the spot and on the futures. This correlation is estimated from the same historical data used to estimate the mean and standard deviations of the continuously compounded returns on the spot and futures.

ε_1 and ε_2 are simulated as follows:

$$\varepsilon_1 = x_1,\ x_1 \sim \Phi(0,1) \qquad (30)$$

$$\varepsilon_2 = \rho_{12}x_1 + x_2\sqrt{1-\rho_{12}^2},\ x_2 \sim \Phi(0,1) \qquad (31)$$

where, x_1 and x_2 represent independent standard normal random variables.

A.2. Beer Demand

To simulate the weekly beer demand during the time period T_1, we assume that this demand has a lognormal distribution. The two parameters required to define this distribution are the mean and standard deviation. We obtain the values of these two parameters through private communication with a major brewery. During the simulation runs, a random sample is obtained from this distribution for each iteration.

Appendix B – Notations Used in Modeling

B_{ij}	: level of inventory type i at the beginning of week w_j
c_0	: premium price at t_0 of a call option
d_j	: demand for beer during week w_j (in millions of cans)
E_{ij}	: level of inventory type i at the end of week w_j
f	: factor converting aluminum tons into millions of cans
F_0	: price at time t_0 of aluminum futures with delivery date that follows t_1
F_1	: price at time t_1 of aluminum futures with delivery date that follows t_1
h_i	: weekly holding cost of inventory type i ($/million cans)
	: weekly holding cost of inventory type i, as it moves downstream ($/million cans, $>h_i$)
h_{op}	: weekly holding cost of put and call options
K	: exercise price of the put and call options
L_b	: lead time to replenish beer inventory
L_c	: lead time to replenish cans inventory
M_{bj}	: quantity of beer distributed in the market during week j
N_c	: number of call options on aluminum futures with delivery date that follows t_1
N_p	: number of put options on aluminum futures with delivery date that follows t_1
p_0	: premium price at t_0 of a put option
P_{bj}	: quantity of cans being filled and packed by the brewery during week w_j (in millions)
P_{cj}	: quantity of cans being produced by the supplier during week w_j (in millions)
Q_a	: total quantity of aluminum sheets purchased in period T_0 (in tonnes)
Q_{a0}	: quantity of aluminum sheets purchased at time t_0 (in tonnes)
Q_{a1}	: quantity of aluminum sheets purchased at time t_1 (in tonnes)
Q_{bj}	: quantity of beer cans shipped to the distribution center at time t_j (in millions)
Q_{cj}	: quantity of aluminum cans shipped by the can supplier at time t_j (in millions)
r	: weekly interest-free interest rate
s	: stockout cost due to loss of beer sales ($/unit of unsatisfied demand)
S_0	: aluminum spot price at time t_0
S_1	: aluminum spot price at time t_1
T	: period of time where T {T_0, T_1}
t_j	: point of time where j = {0, 1, …, 13}
v	: value set by the supply chain as a limit for the VaR
VaR	: value at risk of the total expected opportunity cost
w_j	: week starting at time t_j

Chapter 5

Model Extension with Lead Time Variability

5.1 Introduction

This Chapter is a sequel to Chapter 4, where we develop a base model that integrates operational and financial hedging to minimize the expected total opportunity cost, E(TOC), of the supply chain. In the base model, we perform an experimental design to study the effects of three principal factors on the expected total opportunity cost: i) level of risk the supply chain is willing to assume; ii) demand variability, and; iii) volatility of the aluminum price. In this Chapter, we extend the base model by introducing an operational risk factor. In this extension to our base model, as described in Section 5.2, we incorporate a stochastic lead time in the supply of aluminum cans to the brewery.

The main purpose of this Chapter is to study the alterations in the product flows across the supply chain and the consequent change in the opportunity cost in the presence of stochastic lead time. In the base model we assigned a deterministic duration of four weeks for the lead time in supplying empty cans. In this model extension, this lead time has a discrete probability distribution. We study the effects of the lead time variability factor at two levels: high and low. In both cases, the mean lead time duration is four weeks to facilitate comparison with the base model. With a stochastic lead time in our model, an order quantity may not be completely produced on time. Only the completed portion is shipped to the brewery, as planned, at the end of the four weeks duration. The remaining balance is delivered the next week, and accordingly the supplier incurs an additional carrying cost. Under this condition, if the brewery increases the order quantity to avoid shortages in empty cans, the holding costs of these cans increase.

We perform an experimental design that involves, in addition to the three aforementioned factors, lead time variability and model (integrated and sequential). With each factor represented at two levels, we create treatments from all possible permutations of these factors and we find the optimal solutions for these treatments. To examine the impact of the lead time variability on the supply chain performance, we compare the results of the extended model with the results in the base model. We also compare the solutions in the extended model between cases of high and low lead time variability. These comparisons allow us to make general observations on the effects of lead time variability on the opportunity cost, the operational hedging strategy and the product flow. Then, we conduct a factorial analysis on the results of the extended model to gain more insights on the interaction effects of the five factors on the opportunity cost. The generated regression model explains the variations in the opportunity cost. Based on this model, ANOVA is carried out to test the significance of the main and interaction effects of the five factors on the opportunity cost.

In Section 5.2, we explain our method in incorporating lead time variability in our model. We highlight the changes in the production schedules and the product flows due to stochastic lead time and we describe the respective additional costs. Changes in the base model formulations are also presented. In Section 5.3, we discuss the experimental results and make general observations on the impact of lead time variability. In Section 5.4, we perform a statistical analysis where the ANOVA results are provided and the significant effects of the various factors are examined. In Section 5.5, we summarize the main findings and draw some managerial insights.

5.2 Extended model with lead time variability

5.2.1 Incorporating the lead time factor

In the base model, we assume a deterministic lead time in the supply of aluminum cans to the brewery. We considered that, irrespective of the order quantity, the can supplier completes the lot production in exactly four weeks and ships the produced empty cans to the brewery at the beginning of the fifth week. In this model extension, we incorporate uncertainty in the lead time by considering a stochastic lead time with a discrete probability distribution.

5.2.1.1 Variability of the lead time

We consider two levels of lead time variability that we denote as high and low. The high variability corresponds to the case to which we assign probabilities of 0.464, 0.214, 0.179 and 0.143 to lead time durations of 3.5, 4, 4.5 and 5 weeks, respectively. The low variability corresponds to the case in which we assign the same probabilities to lead time durations of 3.75, 4, 4.25 and 4.5 weeks, respectively. With these discrete probability distributions the average lead time duration in both cases is four weeks, the same duration used in the base model. This facilitates the comparison between the base and the extended models. The standard deviations of the discrete probability distributions with high and low variability are 0.551 and 0.275 weeks, respectively.

5.2.1.2 Modeling the stochastic lead time duration

To introduce the variability of the lead time duration into our model, we make a number of assumptions that are specific to the conceptual background of our model. These assumptions are necessary to justify our calculations of the relevant costs. First, we assume that the cans are produced in a continuous process with a production rate that is constant for each batch of cans ordered for the brewery's consumption in a specific week. Second, the variability of the lead time duration stems from a change in this production rate (for example due to increased capacity allocation for another customer), and not from a delay in the production start time or a disruption in the production process. This assumption allows us to determine the quantity of cans produced at the end of the four weeks duration (the expected completion date) in a proportional manner as we will discuss in the following section. Third, we assume that shipments from the can supplier to the brewery are made once a week. This means that any unfinished portions of an order will be shipped with the next week's order. Finally, we assume that no early shipments are allowed. This means that a batch of cans that is completed earlier than the expected delivery date remains at the supplier's premises until the agreed shipping date.

5.2.1.3 Impact of lead time variability on the SCRM process

The introduction of a stochastic lead time duration has an impact on the production schedule and product flows discussed in the base model in which the quantity of aluminum cans shipped to the brewery (Q_c) is equal to the quantity of a production lot that started four weeks earlier (P_c). That is, in the base model, the planned production quantity (P_c) is actually produced and the planned shipment quantity of cans (Q_c) is thus actually delivered. However, in the extended model, the actual produced quantity of cans,

$(P_c)_{Actual}$, may be less than the planned production quantity, P_c, due to a lead time duration longer than four weeks. Consequently, the actual quantity of cans shipped to the warehouse may be less than the planned quantity (Q_c). Under this new situation, the brewery places an order with the can supplier for a quantity of cans (Q_{cj}) that needs to be received at the beginning of week w_j. The can supplier starts producing this planned quantity, P_c, four weeks before the expected delivery time. In the event that the lead time duration, represented by X, is longer than the expected four weeks, only a proportion of the ordered quantity would be ready for shipment. This proportion is equal to P_c x 4/X. The remaining balance that is still in production is shipped with the batch produced for the next week w_{j+1}. In the event that the lead time duration is shorter than four weeks, the supplier holds all the produced quantity and delivers it, as scheduled, at the beginning of week w_j.

5.2.2 Modifications to the base model formulation

As explained above, incorporating a stochastic lead time duration into the model makes the quantity actually produced by the can supplier every week a variable quantity that is not necessarily equal to the planned production lot (P_c). When the lead time is longer than four weeks, a proportion of P_c is produced on time while the remaining balance is still under production, and is shipped when completed the next week. Subsequently, a holding cost for the remaining balance is added to the total opportunity cost calculations. Accordingly, equation (7) in the base model is modified. The first term in this formulation represents the present value of the holding cost associated with carrying the surplus quantity of aluminum cans during the production phase for the whole lead time period. The surplus is determined by the weekly ending inventory. In other words, this holding cost is the cost of insurance against uncertain demand. We only include the carrying cost corresponding to this surplus quantity, and not to the whole production lot, to be consistent with our definition of the opportunity cost. All the components of the opportunity cost penalize the supply chain for the deviations from ‘perfect’ decisions. Such decisions can be made only if ’perfect’ information on demand quantity and aluminum price is known a priori, which, of course, can never be the case in reality. In accordance with the opportunity cost concept that we adopt, we add to the cost in equation (7) the holding cost corresponding to the proportion of the production quantity that is delayed due to a longer lead time. This cost is perceived as the cost of insurance against uncertain lead time in supplying the cans. To determine this cost, we compute for every production week the actual quantity produced and, correspondingly, the remaining balance quantity still in production. These quantities are computed as follows.

$$(P_c)_{Actual} = \begin{cases} P_c \text{ if } \tilde{L}_c \le 4 \\ P_c \times \dfrac{4}{\tilde{L}_c} \text{ if } \tilde{L}_c > 4 \end{cases} \qquad \text{(i)}$$

The balance in production, BIP = $P_c - (P_c)_{Actual}$ (ii)

Substituting the value of $(P_c)_{Actual}$ in (ii) by the relevant values from (i), the balance in production is determined as follows.

$$BIP = \begin{cases} 0 \text{ if } \tilde{L}_c \le 4 \\ P_c\left(1 - \dfrac{4}{\tilde{L}_c}\right) \text{if } \tilde{L}_c > 4 \end{cases} \qquad \text{(iii)}$$

As justified above, the cost of carrying this balance for four weeks is added to the cost of carrying the quantity produced in surplus. These two costs are calculated in (7a).

$$\sum_{j=}^{8}\left(E_{c(j+\ )} + P_{cj}\mathrm{Max}\left\{\left(\ -\frac{4}{\widetilde{L}_c}\right)\ )\right\}\ u_0 h_{c0} + u_1 h_{c1}\right) \times e^{-r(T_0+\ )} \tag{7a}$$

$$\sum_{j=5}^{13} E_{cj}\left(u_0 h'_{c0} + u_1 h'_{c1}\right) e^{-r(T_0+j)} \tag{7b}$$

The cost in (7b) corresponds to the cost of carrying the surplus quantity of cans in the warehouse. The cost of carrying inventory in a downstream location along the supply chain would be higher than the cost of carrying the same inventory in an upstream location.

5.3 Experimental Design and Discussions of Results

5.3.1 Experimental Design

To study the impact of the lead time variability on the model performance, in the presence of the other three factors incorporated in the base model (VAR, SDD & APV), we perform an experimental design in which each of the four factors is represented at two levels. Table 5.1 provides the values of the four factors used in the experimental design.

Table 5.1 Descriptions of experimental design factors

Factor	Designation	Code	Level		Units
			L	H	
Value-at-risk	VAR	A	1.5	1.8	Million dollars
Demand uncertainty	SDD	B	3.8	4.5	Million cans
Aluminum price volatility	APV	C	(21.3 , 20.3)	(28.8 , 27.4)	%
Lead time variability	LTV	E	0.275	0.551	Weeks

Similar to the optimizations in the base model, we found the optimal solutions for the extended model under different treatments. The results are presented in Table 5.2.

Table 5.2 Optimization Results

Factor Level				Sequential Model											Integrated Model						
				Operational Sub-model					Financial Hedging Sub-model												
VAR	SDD	APV	LTV		E(TOC)	Dev	Q_{a0}	Q_{a1}		E(TOC)	Dev	N_p	N_c		E(TOC)	Dev	Q_{a0}	Q_{a1}	N_p	N_c
1.5	3.8	L	0.275	O01	655.4	553.2	51.2	123.1	S01	637.6	800.0	3,655	715	I01	610.5	851	45.7	129.8	3,981	872
			0.551	O02	687.0	558.0	58.4	115.1	S02	680.9	608.7	1,154	156	I02	663.7	792	62.9	113.5	3,784	94
		H	0.275	O03	654.9	595.2	51.1	123.1	S03	655.7	780.8	2,538	1,113	I03	628.0	769	45.9	129.8	2,152	983
			0.551	O04	700.7	567.8	62.1	112.6	S04	701.8	631.5	1,327	665	I04	692.8	783	65.9	112.0	2,830	433
	4.5	L	0.275	O05	803.6	586.0	65.0	114.6	S05	798.6	645.5	1,676	641	I05	790.2	629	60.5	119.7	1,288	1,083
			0.551	O06	820.8	583.4	67.4	113.9	S06	822.3	600.6	672	238	I06	822.8	645	68.4	112.5	1,805	679
		H	0.275	O07	827.3	572.9	73.6	104.4	S07	827.9	620.7	1,129	386	I07	799.8	653	60.7	120.2	1,238	1,093
			0.551	O08	854.9	565.9	77.9	102.8	S08	857.3	566.0	3	0	I08	842.8	622	70.9	110.9	1,137	857
1.8	3.8	L	0.275	O09	536.3	697.4	13.2	161.5	S09	510.7	1,037.0	4,000	434	I09	508.9	1,034	13.1	162.2	4,000	414
			0.551	O10	566.0	729.7	14.7	162.4	S10	543.8	1,033.2	4,000	819	I10	535.1	1,018	19.0	157.6	4,000	320
		H	0.275	O11	610.2	741.5	34.4	153.3	S11	607.6	1,006.4	3,067	1,116	I11	551.4	1,056	18.4	157.7	3,257	1,350
			0.551	O12	649.7	644.9	45.4	132.1	S12	632.0	1,045.4	3,835	665	I12	573.5	991	19.5	155.6	2,654	1,090
	4.5	L	0.275	O13	721.3	720.1	34.7	142.8	S13	719.7	812.0	2,170	1,084	I13	650.5	1,012	19.4	158.9	3,980	1,186
			0.551	O14	733.4	714.4	35.4	143.3	S14	731.5	824.6	2,376	1,061	I14	664.5	1,010	20.3	159.4	3,989	1,187
		H	0.275	O15	760.1	705.1	49.6	126.9	S15	757.8	805.7	1,609	541	I15	677.9	905	19.7	159.1	1,715	1,362
			0.551	O16	770.7	684.5	50.3	127.6	S16	762.2	916.8	2,848	784	I16	695.2	893	20.5	159.8	1,645	1,363

5.3.2 Impact of Lead Time Variability

To avoid repeating our previous discussion on the base model results, in this section we only emphasize the significant changes in the supply chain performance attributed to lead time variability.

5.3.2.1 Increase in opportunity cost

While it is expected that lead time variability would increase the opportunity cost, our results reveal that this impact may not be significant under certain conditions. First, we compare the opportunity costs of the integrated model with lead time variability incorporated (extended model) with the opportunity costs in the corresponding treatments of the integrated model without lead time variability (base model). Table 5.3 shows the percentage increase in the expected total opportunity cost when lead time variability is incorporated. This increase, however, is statistically not significant in some instances. While in all the treatments with VAR 1.5, except one, the increase in the expected opportunity cost is significant, this is not always the case when VAR is 1.8. Under this lower risk aversion level, only a high lead time variability significantly increases the opportunity cost. This increase is higher when the demand uncertainty is lower.

Table 5.3 Percentage increase in E(TOC) in presence of lead time variability

		VAR: 1.5		VAR: 1.8	
		LTV: L	LTV: H	LTV: L	LTV: H
SDD: 3.8	APV: L	5.3%*	14.5%*	3.8%	9.1%*
	APV: H	0.8%	11.2%*	4.0%	8.2%*
SDD: 4.5	APV: L	7.2%*	11.6%*	3.5%	5.9%*
	APV: H	5.4%*	11.1%*	3.0%	5.6%*

* Statistically significant at 0.05 significance level

Second, we compare the opportunity costs of the integrated extended model between the differing treatments. Table 5.4 shows the percentage increase in the expected total opportunity cost for the various treatments when lead time variability is higher. This increase is, however, found not to be statistically significant for the instances of higher demand uncertainty at the lower risk aversion level. At both risk aversion levels, the increase in total opportunity cost is higher when the demand uncertainty is lower. This conclusion is consistent with the finding reported in Table 5.3.

Table 5.4 Percentage increase in E(TOC) when LTV is higher

		VAR: 1.5	VAR: 1.8
SDD: 3.8	APV: L	9.4%*	5.5%*
	APV: H	10.1%*	4.6%*
SDD: 4.5	APV: L	4.0%*	2.3%
	APV: H	5.7%*	2.3%

* Statistically significant at 0.05 significance level

5.3.2.2 Overall Superiority of the Integrated Model over the Sequential Model

In this section, we study the impact of lead time variability on the superiority of the integrated model over the sequential model. Table 5.5 depicts the percentage difference in the expected opportunity cost between the integrated model and the sequential model in the presence of lead time variability.

Table 5.5 Percentage difference in E(TOC) between integrated and sequential model with LTV

		VAR: 1.5		VAR: 1.8	
		LTV: L	LTV: H	LTV: L	LTV: H
SDD: 3.8	APV: L	4.3%*	2.8%*	0.4%	1.6%
	APV: H	3.4%*	1.4%	8.8%*	8.8%*
SDD: 4.5	APV: L	1.1%	0.0%	9.9%*	9.1%*
	APV: H	3.6%*	2.0%*	10.7%*	9.0%*

* Statistically significant at 0.05 significance level

First, we compare the superiority of the integrated model for differing treatments and for different lead time variability within the extended model. We observe that at the higher risk aversion level, the superiority of the integrated model is higher when the lead time variability is lower. At the lower risk aversion level, the lead time variability does not significantly affect the integrated model's superiority. Second, we compare the superiority of the integrated model for differing treatments in the base model and the extended model. The overall observations made for the base model also apply to the extended model. That is, the integrated model outperforms the sequential model mostly when the risk aversion level is higher. However, we observe a change in the conditions under which the integrated model is better. While in the base model, there was no significant superiority under a low demand uncertainty and a high risk aversion level, such superiority is found to be significant in the presence of lead time variability.

The finding that the integrated model in the presence of lead time variability still outperforms the sequential model is important. Even in the presence of a risk which is traditionally managed by operational approaches, the integrated approach still proves to be superior.

5.3.2.3 Operational Hedging Strategy

In this section, we study the impact of lead time variability on the operational hedging strategy. Table 5.6 shows the ratio (u_0) of the quantity of aluminum sheets purchased at t_0 over the total quantity purchased over the period T_0. This ratio reflects the extent of hedging against aluminum price increases that the supply chain executes using the operational approach. The range of percentages in each cell of the table encompasses values of u_0 at the two levels of APV for each treatment.

Table 5.6 Ratio (u_0) of aluminum sheets purchased at t_0 to total purchased quantity

		VAR: 1.5		VAR: 1.8	
		Integrated	Sequential	Integrated	Sequential
SDD: 3.8	LTV: L	26%	29%	7-10%	8-18%
	LTV: H	36-37%	34-36%	11%	8-26%
SDD: 4.5	LTV: L	34%	36-41%	11%	20-28%
	LTV: H	38-39%	37-43%	11%	20-28%

First, we observe, within the extended model treatments, how the operational hedging strategy varies at the two levels of lead time variability. We note that higher lead time variability increases u_0 for both the integrated and sequential models. However, this observation is valid mainly for the case of a high risk aversion level. Second, we compare the hedging strategy between treatments in the extended model and the corresponding treatments in the base model. We also observe that in the presence of lead time variability, only a more risk averse supply chain uses more operational hedging. A less risk averse supply chain would not significantly change its operational hedging when the lead time is variable, especially for the case of high demand variability.

5.3.2.4 Change in the product flow across the supply chain

An important change in the model performance in the presence of lead time variability is related to the product flow across the supply chain. In the base model, the can supplier converts all the aluminum quantity purchased (Q_a) into cans and ships them to the warehouse (Q_c). The brewery fills all these cans with beer and sends them to the distribution center (Q_b). That is, $Q_a = Q_b = Q_c$. On the other hand, under a stochastic lead time, a larger quantity of aluminum is purchased and converted into cans. Such an action is expected to mitigate against shortages of aluminum cans due to delays in shipment of a proportion of the ordered quantity. However, a portion of these empty cans is left in the warehouse unused. That is, $Q_a = Q_c > Q_b$. Such a situation is justified due to higher carrying cost of beer.

Table 5.7 shows eight different treatments and Figure 5.1 depicts the product flows in the base and extended models under these treatments. In each treatment, the first column represents the quantities flowing in the base model (B), the second and third columns represent the flows in the extended model with a low lead time variability (EL), and the fourth and fifth columns represent the flows in the extended model with a high lead time variability(EH). In the base model Q_a, Q_b and Q_c are equal and thus represented in a single column (Q_a-B). In the extended model, Q_a and Q_c are equal and represented in single column (Q_a-EL, Q_a-EH), while Q_b is represented in a separate column (Q_b-EL, Q_b-EH). A number of observations can be made. First, when the risk aversion level is low, a lower product flow occurs across the supply chain. Second, under the same risk aversion level, a larger flow is observed when the demand variability increases. Third, a higher lead time variability requires a larger quantity of empty cans to be dispatched to the warehouse. However, this variability has a lower impact on the quantity of beer moved to the distribution center.

Table 5.7 Description of treatments depicted in Figure 5.1

Treatment	VAR	SDD	APV	Treatment	VAR	SDD	APV
T1	1.5	3.8	L	T5	1.8	3.8	L
T2	1.5	3.8	H	T6	1.8	3.8	H
T3	1.5	4.5	L	T7	1.8	4.5	L
T4	1.5	4.5	H	T8	1.8	4.5	H

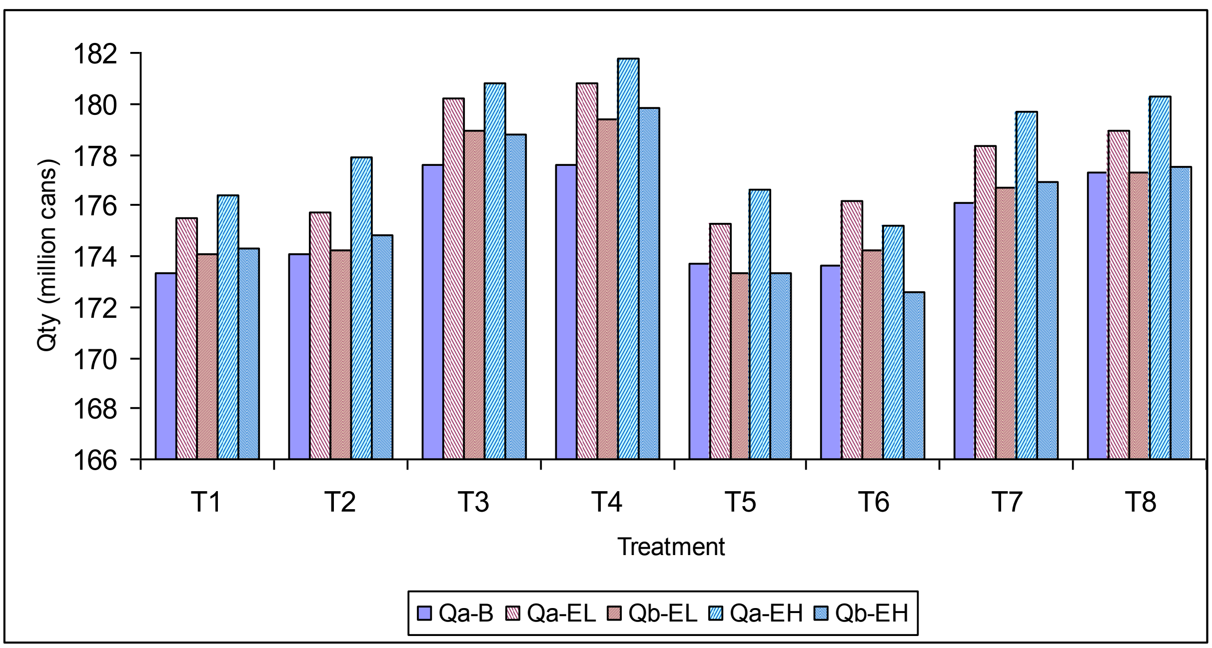

Figure 5.1 Product flows in the base and extended models

5.4 Statistical Analysis

The findings on the effects of lead time variability which are discussed above are based on general observations for the optimization results and presented in Table 5.2. We based our observations on comparisons made between treatments with and without lead time variability, and between treatments with different levels of lead time variability. However, to have better insights on the effects of lead time variability on the supply chain performance we need to study the interaction effects with the other three factors. That is, we need to understand how the impact of lead time variability changes when the other factors vary.

Similar to the analysis carried out in the base model, we conduct a factorial analysis on the extended model using Design Expert®. The four factors presented in Table 5.1 are: value at risk (A), demand uncertainty (B), aluminum price volatility (C) and lead time variability (E). In addition to these four factors , the model factor (coded as D) is incorporated in the analysis as a categorical factor with two values: integrated and sequential. The software generates a linear regression model that explains the variations in the response variable E(TOC). The linear regression model includes terms representing the five factors in addition to interaction terms. The linear regression model can be used to predict the value of the response variable for any combination of the factors within their corresponding lower and upper levels. We refer to the linear model as the regression model to avoid confusion with the original hedging models used for optimization.

5.4.1 Regression Model

The software runs ANOVA to test for the overall model fit and for the significance of the effects of each term in the model on the response variable. Table 5.8 presents part of the

ANOVA results for the regression model. Considering the main objective of this chapter, we show specifically the terms that include lead time variability (factor E). In addition to the main effects of the factors, the interaction between factors have significant effects on E(TOC). The table shows that lead time variability has a significant effect on the opportunity cost. Most of the interaction terms that include lead time variability are found to be significant. However, few of these interaction terms are not significant (CE, ABE and BDE). We discuss the significant interactions involving lead time variability and provide managerial insights in the following sub-section.

Table 5.8 Part of ANOVA results for the linear regression model

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	3,219,451	26	123,825	9,298	< 0.0001
A-VAR	914,057	1	914,057	68,638	< 0.0001
B-SDD	1,933,191	1	1,933,191	145,166	< 0.0001
C-APV	102,418	1	102,418	7,691	< 0.0001
D-Model	91,017	1	91,017	6,835	< 0.0001
E-LTV	74,826	1	74,826	5,619	< 0.0001
AE	10,409	1	10,409	782	< 0.0001
BE	5,852	1	5,852	439	< 0.0001
CE	56	1	56	4	0.0406
DE	1,016	1	1,016	76	< 0.0001
ABE	132	1	132	10	0.0018
ACE	702	1	702	53	< 0.0001
ADE	640	1	640	48	< 0.0001
BDE	104	1	104	8	0.0055
CDE	260	1	260	20	< 0.0001
ABDE	293	1	293	22	< 0.0001

5.4.2 Interaction effects of lead time variability

The main effects of lead time variability on the opportunity cost were presented in Tables 5.3 and 5.4 above. As expected, in general, the results reveal that lead time variability has a positive correlation with the opportunity cost. However, this effect is found not to be significant under certain conditions. To explain the variations in the impact of lead time variability on the expected opportunity cost, we study the interaction effects of lead time variability with other factors.

5.4.2.1 Two-way interactions

The ANOVA table shows that the interaction of the lead time variability with the factors of risk aversion level, demand uncertainty and model factor is found to be significant on E(TOC). These two-way interactions are represented by the terms AE, BE and DE in the regression model. Figure 5.2 depicts one example illustrating each of these three interactions.

The results reveal that, under any treatment condition, an increase in lead time variability amplifies the effect of the risk aversion level on the opportunity cost. Figure 5.2a illustrates an example of such amplification for the integrated model. Under low demand uncertainty and high aluminum price volatility, when the risk aversion level decreases from \$ 1.5 million to \$ 1.8 million, the decline in the expected opportunity cost is a function of the lead time variability level. The decline is \$ 78,000 at a low level of lead time variability and \$ 118,000 at a high level of lead time variability. These figures are calculated by subtracting the costs at the two ends of each line in Figure 5.2a. The software allows the user to read these costs by placing the cursor on the endpoint of a line.

In contrast, an increase in lead time variability diminishes the effect of demand uncertainty on the expected opportunity cost. Figure 5.2b illustrates an example of such a reduction for the integrated model. Under a high risk aversion level and a low aluminum price volatility, when the demand standard deviation increases from 3.8 million cans to 4.5 million cans, the increase in the expected opportunity cost is largely a function of lead time variability level. This increase is \$ 180,000 at a low level of lead time variability and \$ 159,000 at a high level of lead time variability.

The impact of the lead time variability on the expected opportunity cost is higher in the integrated model than in the sequential model. Figure 5.2c illustrates the difference in the impact between the two models. Under a high risk aversion level, a low demand uncertainty and a high aluminum price volatility, the increase in the expected opportunity cost as the lead time variability increases is $ 64,000 in the integrated model and $ 47,000 in the sequential model.

On the other hand, the ANOVA results show that the interaction between the lead time variability and aluminum price volatility (term CE) is not significant. That is, the lead time variability does not alter the effects of the aluminum price volatility on the opportunity cost. This outcome is in line with everyday operational reality.

5.4.2.2 Three-way interactions

To further study the variations in the impact of lead time variability on the effects of the other factors on the expected opportunity cost, we examine the three-way interactions involving lead time variability. The ANOVA table shows that there are three three-way interactions involving lead time variability that are significant. These significant interactions are: i) value at risk – aluminum price volatility – lead time variability (term ACE), ii) value at risk – model – lead time variability (term ADE), iii) aluminum price volatility – model – lead time variability (term CDE).

The interaction term ACE is the change in the impact of the lead time variability on the effect of the risk aversion level on the expected opportunity cost, when the aluminum price volatility changes. Figure 5.3 presents an example that illustrates this three-way interaction in the integrated model under low demand uncertainty. In the case of low aluminum price volatility, Figure 5.3a depicts the decline in the expected opportunity cost as the risk aversion level decreases. A decline is shown for each level of lead time variability and the difference between the two declines is \$ 28,000. That is, the impact of lead time variability on the decreasing effect of the risk aversion level on the expected opportunity cost is found to be \$ 28,000. In the case of a high aluminum price volatility, this impact is \$ 40,000, as illustrated in Figure 5.3b.

The interaction term ADE is the change in the impact of the lead time variability on the effect of the risk aversion level on the expected opportunity cost, when the model changes from integrated to sequential, or vice versa. Figure 5.4 presents an example that illustrates this three-way interaction under a low demand uncertainty and a high aluminum price volatility. In the case of the integrated model, Figure 5.4a depicts the decline in the expected opportunity cost as the risk aversion level decreases. A decline is shown for each level of lead time variability and the difference between the two declines is \$ 40,000. That is, the impact of lead time variability on the decreasing effect of the risk aversion level on the expected opportunity cost is found to be \$ 40,000. In the case of the sequential model, this impact is \$ 22,000, as illustrated in Figure 5.4b.

The interaction term CDE is the change in the impact of the model factor on the effect of the lead time variability on the expected opportunity cost, when the aluminum price volatility changes. Figure 5.5 presents an example that illustrates this three-way interaction under a high risk aversion level and a high demand uncertainty. In the case of a low aluminum price volatility, Figure 5.5a depicts the increase in the expected opportunity cost as the lead time volatility increases. An increase is shown for each model and the difference between the two increases is \$ 8,000. That is, the impact of the model factor on the increasing effect of lead time variability on the expected opportunity cost is found to be \$ 8,000. In the case of a high aluminum price volatility, this impact is \$ 16,000, as illustrated in Figure 5.5b.

Some interaction terms involving lead time variability are found not to be significant by ANOVA. Finding the term ABE not significant means that the impact of lead time variability on the effect of the risk aversion level on the expected opportunity cost does not change when the demand uncertainty changes. Finding the terms BCE and BDE not significant means that the impact of lead time variability on the effect of the demand uncertainty on the expected opportunity cost does not change when the aluminum price volatility changes or when the model used changes.

5.4.2.3 Four-way interaction

The term ABDE is the only four-way interaction involving lead time variability that is found to be significant by ANOVA. We interpret this interaction as the change in the three-way interaction ABE as the level of factor D changes. In the sequential model, the impact of lead time variability on the effect of the risk aversion level on the expected opportunity cost (term ABE) changes only by \$ 2,000 between the two levels of demand uncertainty. However, in the integrated model, the same impact changes by \$ 12,000 between the two levels of demand uncertainty.

5.4.2.4 Managerial insights

Considering the main effect of lead time variability on the expected opportunity cost, it is evident that the supply chain would perform better by reducing this variability. This task calls for strong collaboration among the supply chain members. The brewery needs to share demand forecast information with the can supplier to facilitate the supplier's production schedule. In turn, the can supplier needs to show commitment to comply with the fluctuating weekly quantities. When lead time variability is unavoidable, decisions should then be made in accordance with the insights that the interaction effects of lead time variability with the other factors provide.

As we discussed above, lead time variability intensifies the impact of the risk aversion level on the expected opportunity cost. That is, with higher lead time variability, the improvement in the expected opportunity cost becomes more pronounced when the risk aversion level is lower. This observation is explained by the ability of less risk averse supply chain to exploit uncertainties to minimize its expected opportunity cost. With lead time variability, the uncertainty increases and, in turn, the payoff from exploiting this uncertainty would increase. Similar interaction is observed with demand uncertainty. A supply chain can reduce the expected opportunity cost by being less risk averse, and the reduction would be larger under high demand uncertainty than under low demand uncertainty. The regression analysis confirms this argument. In the event that the supply chain cannot reduce the lead time variability, being less risk averse would balance the negative effect of lead time variability. Figure 5.2a illustrates this case with numerical example. If the supply chain is more risk averse, the expected opportunity cost increases by $ 64,000 when lead time variability increases. On the other hand, if the supply chain is less risk averse, the difference in the opportunity cost would be only $ 24,000. Furthermore, based on the three-way interactions discussed above, the supply chain would be even more compelled to be less risk averse when the aluminum price volatility is higher.

The decreasing impact of lead time variability regarding the effect of demand uncertainty on the opportunity cost makes it less compelling for a supply chain operating under high demand uncertainty to work on reducing the lead time variability. Figure 5.2b, for example, shows that under low demand uncertainty an increase in lead time variability increases the opportunity cost by \$ 53,000. This increase drops to \$ 32,000 under high demand uncertainty. This is explained by the connection between the response of the supply chain to an increase in demand uncertainty and its response to an increase in lead time variability. When demand uncertainty increases, the supply chain would increase the beer quantity in the distribution center. Such increase necessitates a corresponding increase in cans quantity. The latter increase would also be necessary to mitigate higher variability in lead time.

5.5 Conclusion

In this Chapter, we study the changes in the product flows due to variability in the lead time of the supply of empty cans to the brewery. We also examine the impact of stochastic lead time on the expected opportunity cost and on the hedging decisions. In this model extension to the base model, we change the four-week deterministic duration to supply empty cans to the brewery to a stochastic duration following discrete probability distribution with a mean of four weeks lead time.

We generate 16 treatments from the permutations of the four factors: value-at-risk, demand uncertainty, aluminum price volatility, and lead time variability. Each factor is represented at two levels. We solve these treatments using the integrated model and the sequential model. In the analyses of results, we focus on the effects of lead time variability as this is the main purpose of this Chapter. Based on experimental findings, we make a number of observations. While it is expected that lead time variability increases the opportunity cost, the results reveal that this increase may not be significant under certain conditions. For example, under low risk aversion level, only high lead time variability would significantly increase the opportunity cost. Furthermore, while expecting that a high lead time variability would result in a larger increase in opportunity cost than a lower lead time variability, results reveal that this may not be the case under high demand uncertainty and low risk aversion level. This is explained by the dominating effects of the latter two factors, at these respective levels, on the expected opportunity cost, as revealed in the regression analysis.

Knowing that the risk of stochastic lead time is traditionally managed with operational tools, it is important to note that the integrated model is found to outperform the sequential model under lead time variability. The superiority of the integrated model is, however, not influenced by the lead time variability level when the supply chain is less risk averse. In both the integrated and the sequential models, the results reveal that more risk averse supply chain would use operational hedging more as lead time variability increases.

The statistical analysis sheds more light on the interaction effects of lead time variability with the other factors on the opportunity cost, and hence allows us to draw some managerial insights that can support decisions made by practitioners. In the base model, it was found that lower risk aversion level would decrease the opportunity cost, and that a higher demand uncertainty would increase the opportunity cost. The results in the extended model show that lead time variability amplifies the former effect and reduces the latter. In turn, this impact of lead time variability on the effect of risk aversion level on opportunity cost depends on the aluminum price volatility and on the model used.

The analysis also allows us to better understand the direct effect of lead time variability on the opportunity cost. According to the results, the impact of lead time variability on the opportunity cost is higher in the integrated model than in the sequential model. Furthermore, this impact is found to be positively correlated with the aluminum price volatility.

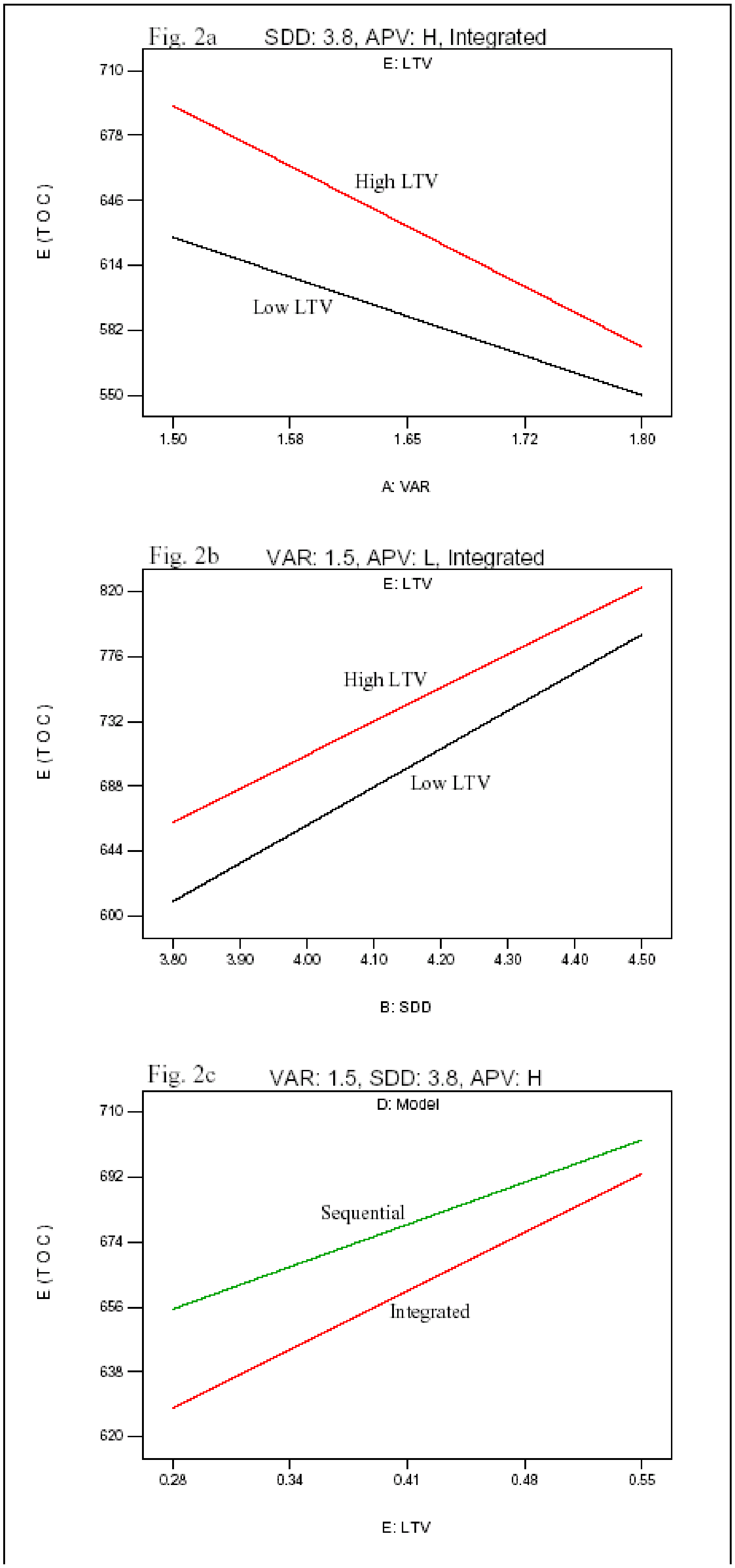

Figure 5.2 Illustrations of AE, BE and DE interactions

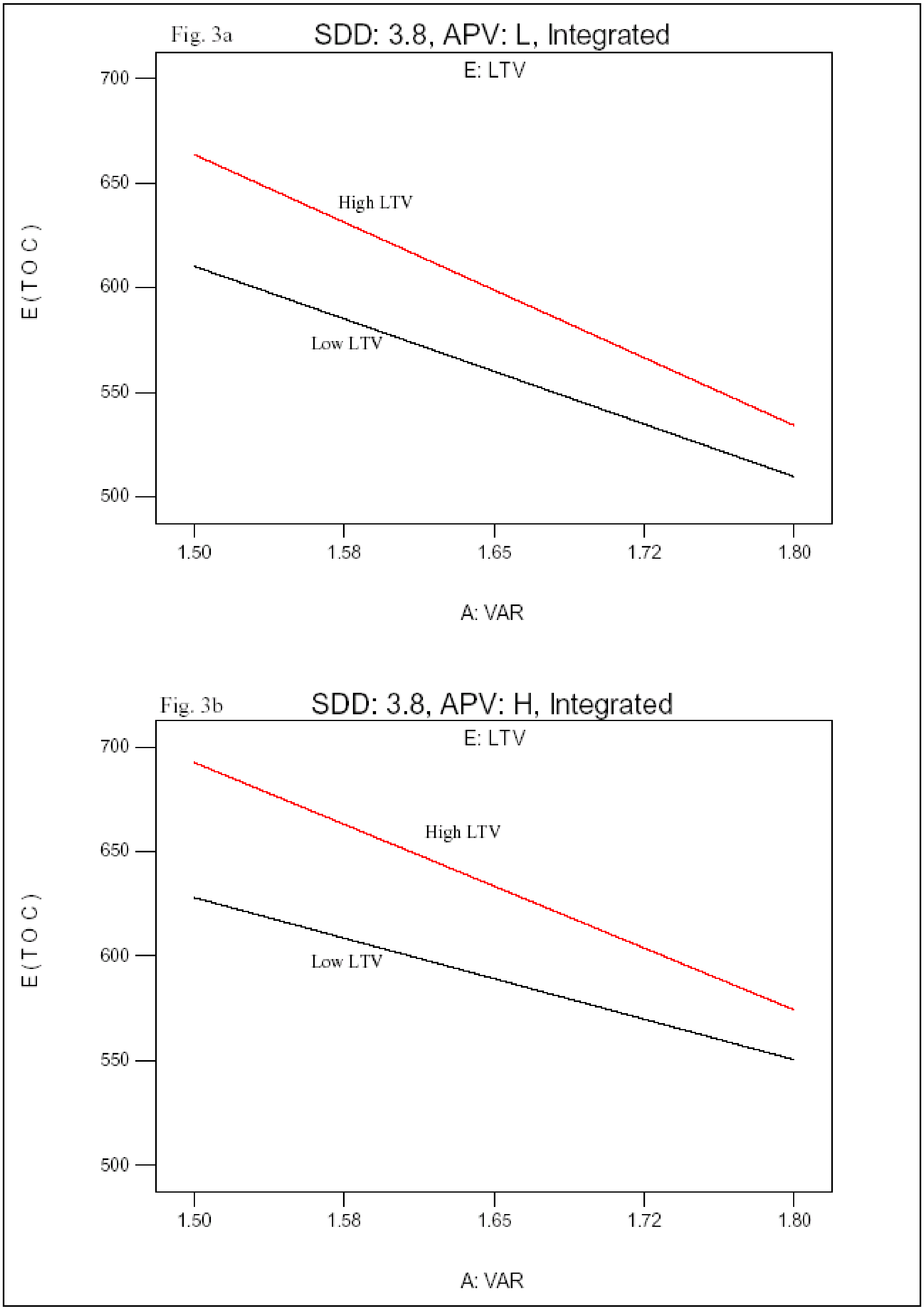

Figure 5.3 Illustration of ACE interaction

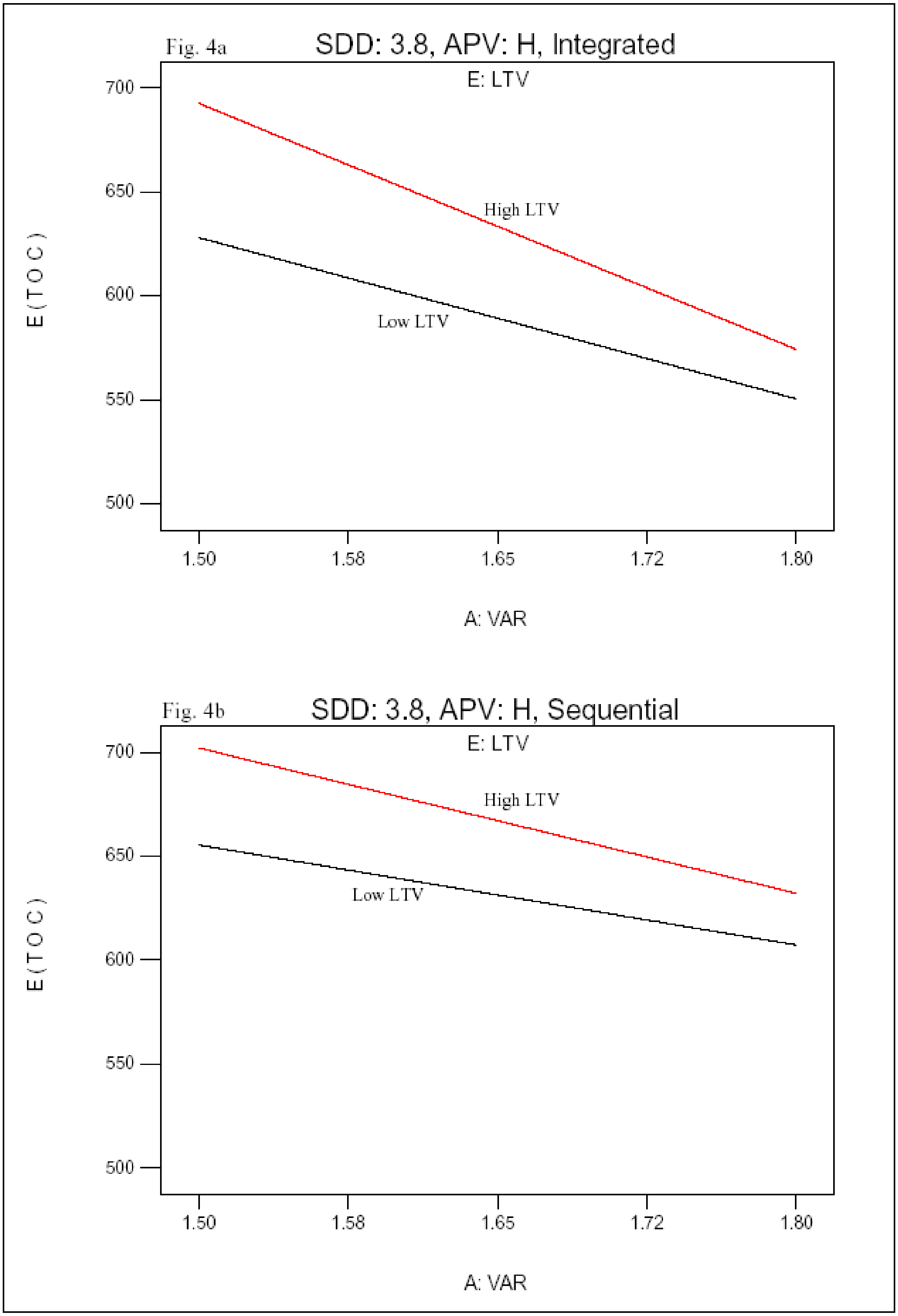

Figure 5.4 Illustration of ADE interaction

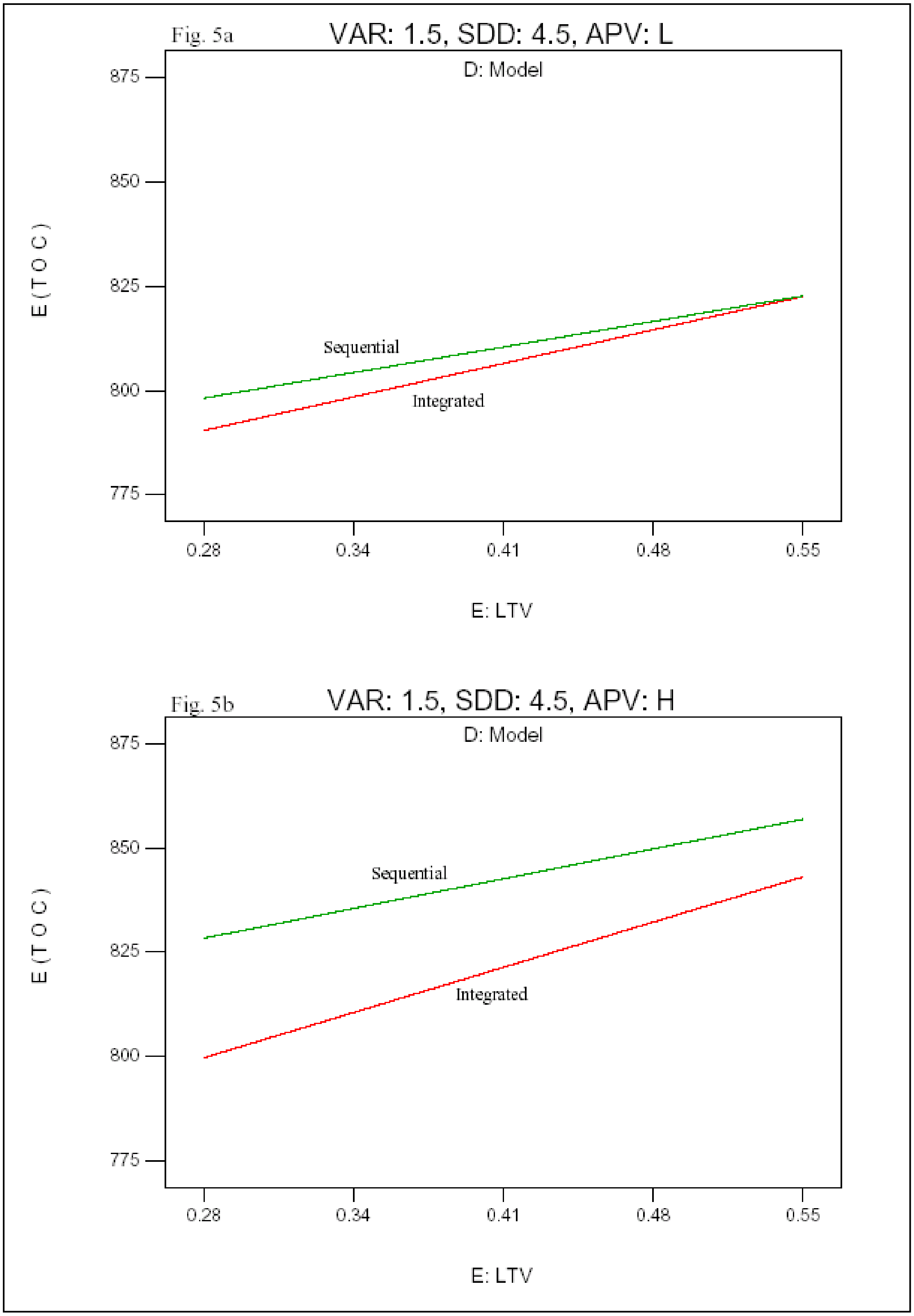

Figure 5.5 Illustration of CDE interaction

Chapter 6

Model Extension with Exchange Rate Risk

6.1 Introduction

This Chapter is a sequel to Chapter 4, in which we develop a base model that integrates operational and financial hedging to minimize the expected total opportunity cost, E(TOC), of the supply chain. In the base model, we perform an experimental design to study the effects of three principal factors on the expected total opportunity cost: i) the level of risk the supply chain is willing to assume; ii) the demand variability, and; iii) the volatility of the aluminum price. In this Chapter, we extend the base model by introducing a financial risk factor. In this extension to our base model, described in Section 6.2, we incorporate the volatility in the Canadian dollar/U. S. dollar (CAD/USD) exchange rate that has an impact on the input price of aluminum.

The main objective of this Chapter is to study the performance of an international supply chain that is exposed to exchange rate risk. The performance of the supply chain is measured in terms of an opportunity cost denominated in CAD. We use historical data on the CAD/USD exchange rate obtained from Datastream to simulate the probable rate that can be observed during the time period covered in our model. As the price of aluminum sheets is denominated in USD, the fluctuations in the exchange rate have a direct impact on inventory decisions. Similarly, as the futures contracts on aluminum are priced in USD, the premium paid to purchase options on these futures and the payoff are affected by the exchange rate. Hence, we use in this extended model options on an underlying asset whose price is the product of the aluminum futures price, denominated in USD, and the CAD/USD exchange rate.

We incorporate the exchange rate in the base model and we start our experiments on the integrated model, setting all the three factors at their base levels. We create various treatments with different volatilities of the exchange rate. We run simulation-based optimizations on these treatments to find the inventory and financial decisions that minimize the total expected opportunity cost. The results prompted us to conduct similar experiments on another set of treatments in which the risk aversion factor is at a higher level. The results from the two sets of experiments shed light on the interaction effects between risk aversion and exchange rate volatility on the supply chain performance. Then, we introduce a new constraint that sets an upper limit for the quantity of aluminum sheets purchased during period T_0 and we find new solutions for the above treatments. The new results allow us to underline the benefits of hedging the exchange rate, and the impacts of risk aversion and exchange rate volatility on these benefits.

In Section 6.2, we explain the new elements in the extended model. We describe how we simulate the exchange rate and discuss its impact on inventory and financial hedging decisions. We introduce a new factor, exchange rate volatility, and discuss the effects of this volatility on the exchange rate and on the index underlying the financial options. We present the changes in the base model formulations. In Section 6.3, we justify the sequence of optimization runs we made in the extended model and we exhibit the corresponding results obtained. We conduct parametric analyses on these results. In Section 6.4, we summarize the main findings and we draw some managerial insights.

6.2 Extended model with exchange rate risk

6.2.1 Incorporating the exchange rate risk factor

In the base model we study the performance of a supply chain operating in one country, the U.S., where all the relevant costs are denominated in USD. In this model extension we incorporate uncertainty in the foreign currency exchange rate as we examine the performance of an international supply chain, consisting of a brewery and a distribution center which operate in Canada and a can supplier which procures aluminum sheets and produces aluminum cans in the U.S. In such a supply chain, all the costs are denominated in CAD. We denote the rate of exchange from USD to CAD at any time t as E_t, where E_t is the number of CAD per USD at time t.

6.2.1.1 Simulating the CAD/USD exchange rate

In the base model we simulated the aluminum spot and futures prices by applying the *Cholesky decomposition* procedure (Hull 2006) for two correlated samples corresponding to these two variables. In this model extension, we follow the same procedure applied for three correlated samples, the exchange rate being the third variable. We use the same correlation between the aluminum spot price and the futures price ($\rho_{12} = 0.9$) that was used in the base model. To determine the correlation between the CAD/USD exchange rate and the spot and futures prices, we used one-year daily historical values of these variables. As in our model, t_0 corresponds to March 31, 2010, we collected the historical data from April 1, 2009, till March 30, 2010. Data on spot and futures prices are obtained from Bloomberg and data on the CAD/USD exchange rate are obtained from Datastream. Figure 6.1 depicts a high correlation between the spot price (S_t) and the CAD/USD exchange rate (E_t). A similar correlation is observed between the futures price (F_t) and the

CAD/USD exchange rate. The correlation coefficient between S_t and E_t (ρ_{13}) and that between F_t and E_t (ρ_{23}) are found to be – 0.87. In our model, to be more conservative, we assumed that $\rho_{13} = \rho_{23} = -0.8$. The procedure followed to simulate these three variables is described in Appendix C.

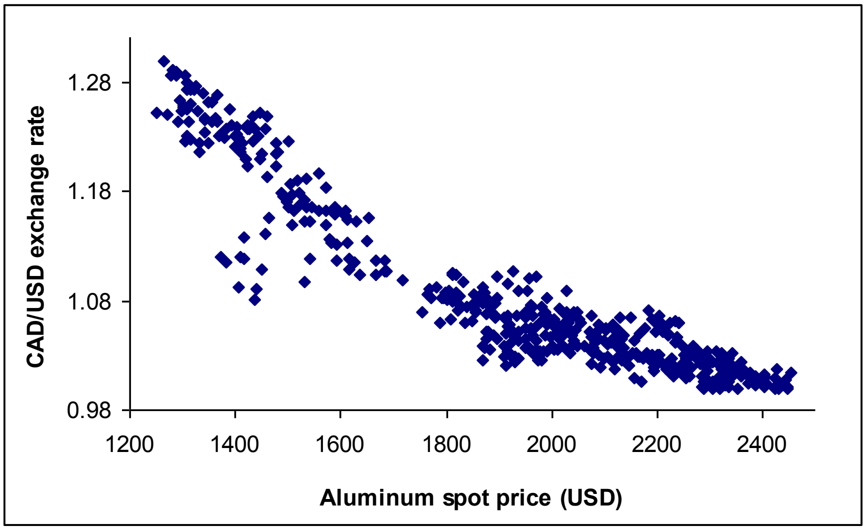

Figure 6.1 Correlation between aluminum spot price and CAD/USD exchange rate

6.2.1.2 Impact of foreign exchange risk on inventory decisions

In the base model, the opportunity costs pertinent to the procurement of aluminum sheets at time t_0 and t_1 are functions of the change in the aluminum price between these two times. While a decrease in this price represents an opportunity cost associated with the quantity Q_{a0}, an increase in the price is an opportunity cost that penalizes the postponement to t_1 of procuring Q_{a1}. In the model extension, these two opportunity costs are functions of the combined effect of the change in the aluminum price and the fluctuation in the CAD/USD exchange rate. The latter can have a significant effect on the aluminum procurement cost denominated in CAD. Figure 6.2 depicts the fluctuation of the exchange rate during the 60 days that precede the date of March 31, 2010, which is the date represented by t_0 in our model. This period is the same that we used in the base model to simulate the aluminum spot and futures prices and its duration is equal to the time period T_0, between t_0 and t_1. The highest point of the graph corresponds to an exchange rate of 1.0745 CAD/USD, on February 8, 2010, and the lowest point corresponds to a rate of 1.0103 CAD/USD, on March 17, 2010. If a quantity of 2,400 tonnes of aluminum was purchased at USD 2,319/tonne when the CAD/USD exchange rate was at its highest, the supply chain would then incur an opportunity cost of CAD 350,000 for not purchasing this quantity when the exchange rate was at its lowest.

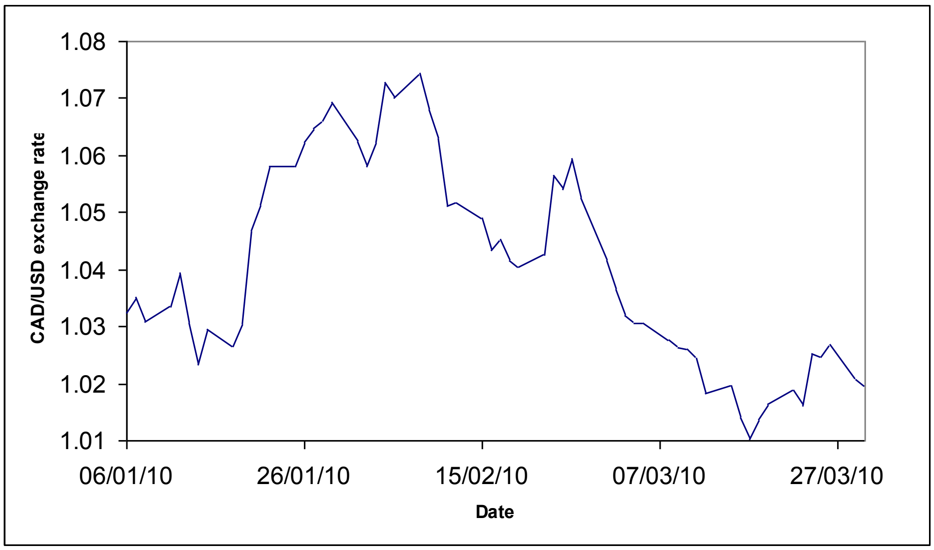

Figure 6.2 Fluctuation of CAD/USD exchange rate from Jan 6 to Mar 30, 2010

6.2.1.3 Impact of foreign exchange risk on financial hedging decisions

The fluctuation in the exchange rate does not only affect the opportunity cost pertinent to the procurement of aluminum sheets, but also affects the opportunity cost corresponding to the purchase of options on aluminum futures. In the base model, we used call and put options to hedge against increases and decreases in the aluminum price, respectively. The opportunity cost associated with these options consists of the premium paid to purchase the options at t_0, less the payoff determined at t_1 from the difference between the strike price and the futures price, if the option is in the money. As the options on aluminum futures and the underlying asset are priced in USD, for a supply chain operating in Canada the premium and the payoff are directly affected by the CAD/USD exchange rate at t_0 and t_1, respectively. Therefore, the fluctuation in the exchange rate is now considered while making the purchase decision of the options on aluminum futures to hedge against aluminum price changes. Figure 6.3 illustrates the movements in the aluminum futures price (F) in the upper tree, and the joint movements of the aluminum futures price and the CAD/USD exchange rate (E) in the lower tree. The numbers on the arrows represent the probabilities of the corresponding movements and the numbers between brackets are the expected values of F and E at t_1 (F_1 and E_1, respectively). In the upper tree, we simulate F_1 10,000 times (same number of iterations as used in the model optimization). The probability of an upward/downward movement is the proportion of cases in which the simulated F_1 is higher/lower than F_0. The upward/downward value of F_1 is the mean value in the cases in which the simulated F_1 is higher/lower than F_0. In the lower tree, we simulate both F_1 and E_1. The probabilities in the first step are determined as in the upper tree. In the second step the conditional probability of an upward/downward movement in E_1, given that F_1 had moved upward, is the proportion of cases (within the specific cases of an upward F_1) in which the simulated E_1 is higher/lower than E_0. Similarly, the conditional probability of an upward/downward movement in E_1, given that F_1 had moved downward, is the proportion of cases (within the specific cases of a downward F_1) in which the simulated E_1 is higher/lower than E_0. The values [F_1, E_1] are the mean values of these two variables in the cases that correspond to the specific joint movements of both F_1 and E_1. For example, F_1 is found to be higher than F_0 in 4,444 out of 10,000 simulation iterations (probability is thus 0.44). Then, within these cases, E_1 is found to be higher than E_0 in 367 cases (probability is thus 367/4444 = 0.08). The mean values of F_1 and E_1 in these 367 cases are $ 2,407 and CAD 1.0303/USD, respectively.

To incorporate the joint movements of the futures price and CAD/USD exchange rate in the analysis underlying the decision to purchase the options, we use in our extended model options on aluminum futures, for which both the futures price and the option price are denominated in CAD. That is, the underlying asset price is the product of the aluminum futures price denominated in USD and the CAD/USD exchange rate. We determine the price of this index (designated as FE hereafter) by the product FxE, where F is the aluminum futures price and E is the CAD/USD exchange rate. Hence, F_0E_0 is the index price at t_0 and F_1E_1 is the price at t_1. The lower tree in Figure 6.3 depicts the paths of the index price. The probabilities and the corresponding expected values in these paths would determine the expected payoff of the index and hence the corresponding option premium. The probability corresponding to a value of F_1E_1 is the joint probability of F_1 and E_1, that is, $P(F_1E_1) = P(F_1) \times P(E_1|F_1)$.

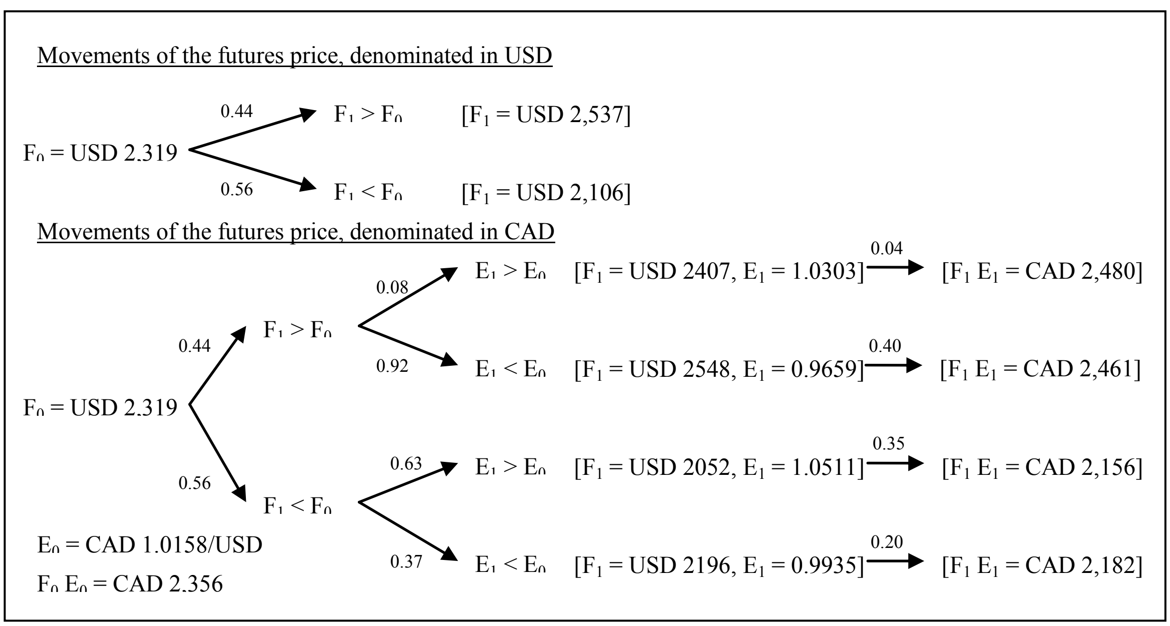

Figure 6.3 Movements of the futures price denominated in USD & the futures price denominated in CAD

6.2.1.4 Volatility of the CAD/USD exchange rate

As described in Appendix C, two parameters used to simulate the CAD/USD exchange rate are the annualized mean (μ_3) and the annualized standard deviation (σ_3) of the continuously compounded return on the currency exchange rate. μ_3 and σ_3 are calculated using historical daily data on the CAD/USD exchange rate obtained from Datastream for a 12 week period in which the last date coincides with the date just prior to the options' purchase date, assumed in our model to be March 31, 2010. The calculated values of μ_3 and σ_3 are -0.051 and 8.4%, respectively.

To better understand the effects of fluctuation in the foreign currency exchange rate, we study the performance of the extended model under different exchange rate volatilities. To do this, we designate the volatility calculated from the actual historical data to be our base volatility and we multiply it by a ratio to increase the volatility by a certain percentage. We use ratios of 1.1, 1.2, 1.3, 1.4, 1.6 and 1.8 in our experiments to increase the base volatility by 10%, 20%, 30%, 40% 60% and 80% respectively. Using each of these ratios, we generate new time series of the CAD/USD exchange rates in which the exchange rate has a volatility equal to the corresponding increased volatility. Figure 6.4 depicts the different paths of the CAD/USD exchange rate with different volatilities over a period of 60 business days (corresponding to our 12 weeks period T_0).

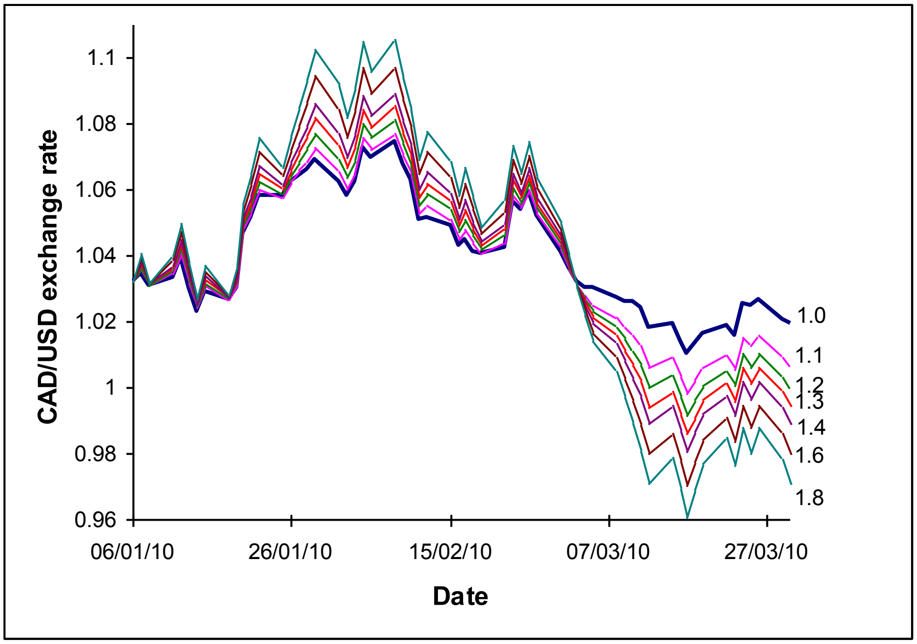

Figure 6.4 CAD/USD exchange rate paths with various volatilities

The numbers at the right end of each graph indicates the volatility ratio. The graph with ratio 1.0 represents the CAD/USD exchange rate path with the actual volatility calculated from the historical data. As can be observed in Figure 6.4, the volatility impact intensifies when the exchange rate exhibits an upward or downward trend. In the first 10 days of our time series, as the exchange rate exhibits an oscillating behavior, the volatility effects are not very significant (small gap between the graphs). The volatility effects are mostly observed in the periods between days 14 and 24 and between days 43 and 54 in which the wide gap between the different paths is caused by periods of upward and downward trends, respectively.

Changing the volatility of the exchange rate (E_t) consequently results in a change in the volatility of the FE index. Using the time series of exchange rates generated for each of the increased volatilities of E_t, we generate corresponding time series of F_tE_t, the value of which equals the product of E_t and F_t. Then we calculate the volatility of F_tE_t as the annualized standard deviation of the continuously compounded return on the index. This volatility is used in the formula for pricing options on the FE index. Table 6.1 summarizes the volatilities of the FX rate (E_t) and the index (F_tE_t).

Table 6.1 Volatilities of the exchange rate E_t and the F_tE_t index

	CAD/USD exchange rate (E_t) volatility ratio						
	1.00	1.10	1.20	1.30	1.40	1.60	1.80
Volatility of the exchange rate E_t	8.40%	9.24%	10.08%	10.92%	11.76%	13.43%	15.11%
Volatility of the index F_tE_t	23.09%	23.11%	23.22%	23.38%	23.56%	24.01%	24.57%

6.2.2 Modifications to base model formulation

As explained above, in this extended model we incorporate foreign exchange risk into our base model. We therefore evaluate our inventory decisions based on the difference in the aluminum spot price, now denominated in CAD. Similarly, as the underlying asset of the options is now the index FE, or the futures price denominated in CAD, we evaluate our decisions to purchase these options based on the premium price now denominated in CAD and the expected payoff due to the change in the index price, again denominated in CAD. Accordingly formulations (1) to (4) in the base model are modified as follows:

The opportunity costs associated with inventories at time t_0 and t_1 are given by:

$$Q_{a0}(S_0E_0 - \tilde{S}_1\tilde{E}_1e^{-rT_0}) + Q_{a0}h_{a0}T_0e^{-rT_0} \tag{1b}$$

$$Q_{a1}(\tilde{S}_1\tilde{E}_1e^{-rT_0} - S_0E_0) \tag{2b}$$

The costs associated with the purchase of put and call options are given by:

$$N_pp_0 + N_pp_0h_{op}T_0e^{-rT_0} - N_pe^{-rT_0}\text{Max}\{(K - \tilde{F}_1\tilde{E}_1), 0\} \tag{3b}$$

$$N_cc_0 + N_cc_0h_{op}T_0e^{-rT_0} - N_ce^{-rT_0}\text{Max}\{(\tilde{F}_1\tilde{E}_1 - K), 0\} \tag{4b}$$

where $K = F_0E_0$ (since the options are assumed to be at the money). p_0 and c_0 are the premiums of put and call options on the FE index, respectively. Similar to calculations of these two prices in the base model, p_0 and c_0 are calculated here also using Black's model (Hull 2006, pp. 332-333) with F_0 replaced everywhere by F_0E_0.

The unit stockout cost and the unit holding costs of aluminum sheets, aluminum cans and canned beer are all denominated in CAD in the extended model. However, the formulations (5) to (8) in the base model do not change. All the other formulations remain the same.

6.3 Results and parametric analyses

In our study of the base model we created 27 treatments for each of the integrated, the operational and the sequential models. These treatments correspond to all possible permutations of the three factors (each at three levels): value-at-risk (VAR), demand uncertainty (SDD) and aluminum price volatility (APV). In order to study the effects of the CAD/USD exchange rate on the performance of the supply chain we incorporated the exchange rate into the integrated base model when all the three factors are at their central levels, that is, VAR = 1.8, SDD = 4.5, APV = B (base level corresponding to aluminum price volatility calculated from historical data). With the three factors at these levels, we generate a set of treatments for the extended model. Each treatment corresponds to one level of the abovementioned exchange rate volatility. As we did in the base model, at each treatment, we run simulation-based optimization to determine the optimal values of our decision variables that would minimize the total opportunity cost of the supply chain. The optimization results are summarized in Table 6.2. In this table and in all the following tables, E(TOC) and the standard deviation (SD) are denominated in CAD, the aluminum quantities are in million cans and the number of options is in tonnes of aluminum.

Table 6.2 Optimization results of extended model with VaR = 1.8

	VAR = 1.8, SDD = 4.5, APV = B						
	CAD/USD exchange rate volatility ratio						
	1.00	1.10	1.20	1.30	1.40	1.60	1.80
E(TOC)	468,154	466,528	461,235	464,999	464,179	451,923	432,489
SD	888,149	873,869	865,948	834,308	851,764	856,666	862,880
Q_{a0}	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Q_{a1}	187.0	199.1	204.2	225.0	227.1	246.4	266.9
Q_a	187.0	199.1	204.2	225.0	227.1	246.4	266.9
N_p	1,518	1,127	981	0	0	0	0
N_c	0	55	0	0	0	0	0

6.3.1 Optimal hedging with and without exchange rate risk

As the costs in the base and extended models are denominated in different currencies we cannot compare the values of E(TOC) in the two models, but we rather compare their operational and financial hedging strategies. In the base model, the optimal values of aluminum quantities and options purchased are (Q_{a0}: 19; Q_{a1}: 158.8; N_p: 3,106; N_c: 1,430). We compare these values to the optimal values of these decision variables in the extended model with an exchange rate volatility ratio of 1.0. When foreign exchange risk is incorporated, the supply chain does not hedge the aluminum price increase with an initial inventory (Q_{a0}), but rather increases the quantity purchased at t_1 (Q_{a1}) and substantially decreases the use of financial hedging (the number of put options, N_p, is reduced by half and the use of call options, N_c, is completely eliminated).

6.3.1.1 Rationale for the change in the operational hedging strategy in the extended model

To explain the change in the operational hedging strategy in the extended model we examine the cumulative probability distribution of the present values (PV) of the aluminum spot price at t_1 in both models, as depicted in Figures 6.5 and 6.6, with delimiters indicating the values of S_0E_0 and S_0. Buying Q_{a0} would yield an opportunity profit when the present value of the aluminum price at t_1 is higher than the price at t_0. The parts of the two curves at the right side of the aluminum price at t_0 indicate the probabilities of opportunity profit. For the same profit value the corresponding probability in the extended model is lower than the probability in the base model. For example, in the base model, $P[PV(S_1) > 2{,}400] = 30.1\%$ which means that $P(\text{profit} > 113) = 0.301$; the profit being equal to $PV(S_1)$ minus the S_0. To have the same profit in the extended model, the present value of the aluminum price should be at 2,436. The probability that the price is higher than this value is 14.5%. Thus $P(\text{profit} > 113) = 0.145$. Similar observations are made for any profit value, leading to the conclusion that the probability of any opportunity profit is lower in the extended model, which explains the decline in Q_{a0}.

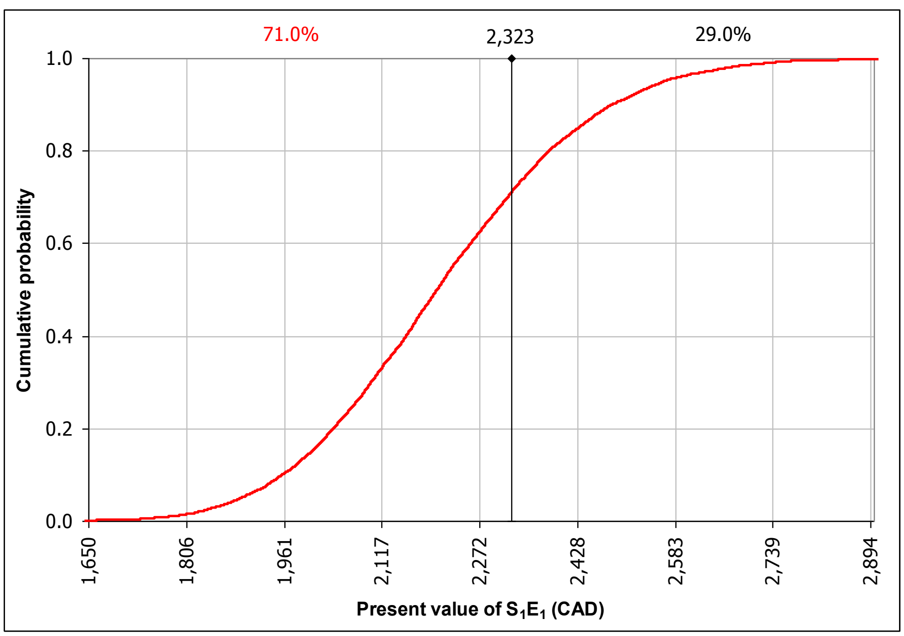

Figure 6.5 Cumulative probability distribution of present value of S_1E_1 in the extended model

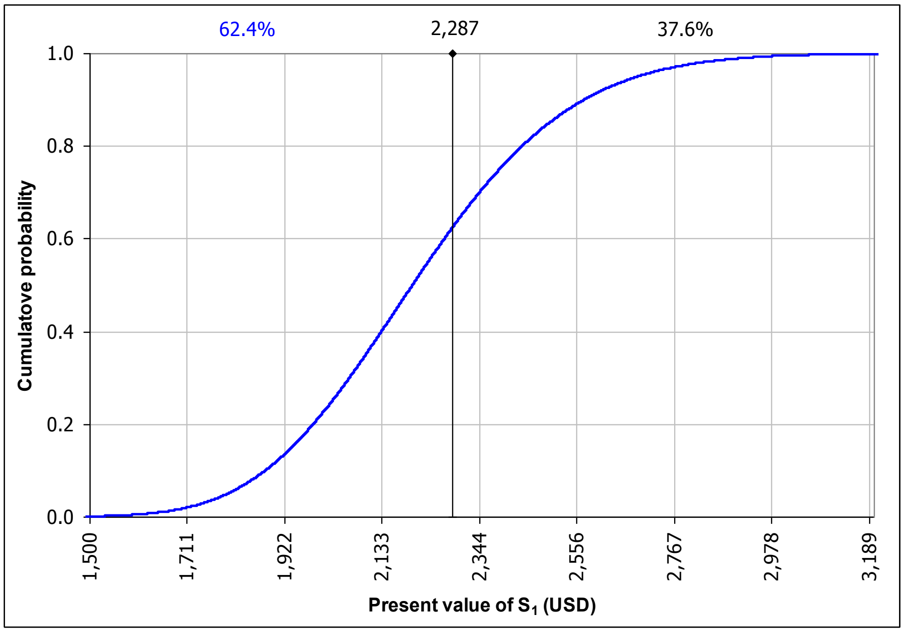

Figure 6.6 Cumulative probability distribution of present value of S_1 in the base model

6.3.1.2 Rationale for the change in financial hedging strategy in the extended model

To explain the change in the financial hedging strategy in the extended model we examine the probability distributions of the futures price at t_1 in both models, as depicted in Figures 6.7 and 6.8, with delimiters indicating the options' strike price. Put options would yield a positive payoff when the futures price at t_1 is lower than the strike price. The parts of the two curves at the left side of the strike price indicate the probabilities of positive payoffs. For the same payoff value the corresponding probability in the extended model is lower than the probability in the base model. For example, in the base model, $P(F_1 < 2{,}000) = 12.8\%$ which means that $P(\text{payoff} > 319) = 0.128$; the payoff being equal to the strike price (2,319) minus the value of F_1. To have the same payoff in the extended model, where the strike price is 2,356 the futures price should be at 2,037. The cumulative probability corresponding to this value is 9.2%. Thus, $P(\text{payoff} > 319) = 0.092$. Similar observations are made for any positive payoff value, leading to the conclusion that the probability of any positive payoff is lower in the extended model, which explains the decline in N_p.

On the other hand, call options would yield a positive payoff when the futures price at t_1 is higher than the strike price. The parts of the two curves at the right side of the strike price indicate the probabilities of positive payoffs. For the same payoff value, the corresponding probability in the extended model is lower than the probability in the base model. For example, in the base model, $P(F_1 > 2{,}500) = 21.7\%$ which means that $P(\text{payoff} > 181) = 0.217$; the payoff being equal to F_1 minus the strike price. To have the same payoff in the extended model, the futures price should be at 2,537. The probability that the futures price is higher than this value is 12.2%. Thus, $P(\text{payoff} > 181) = 0.122$. Similar observations are made for any positive payoff value, leading to the conclusion that the probability of any positive payoff is lower in the extended model, which explains the decline in N_c.

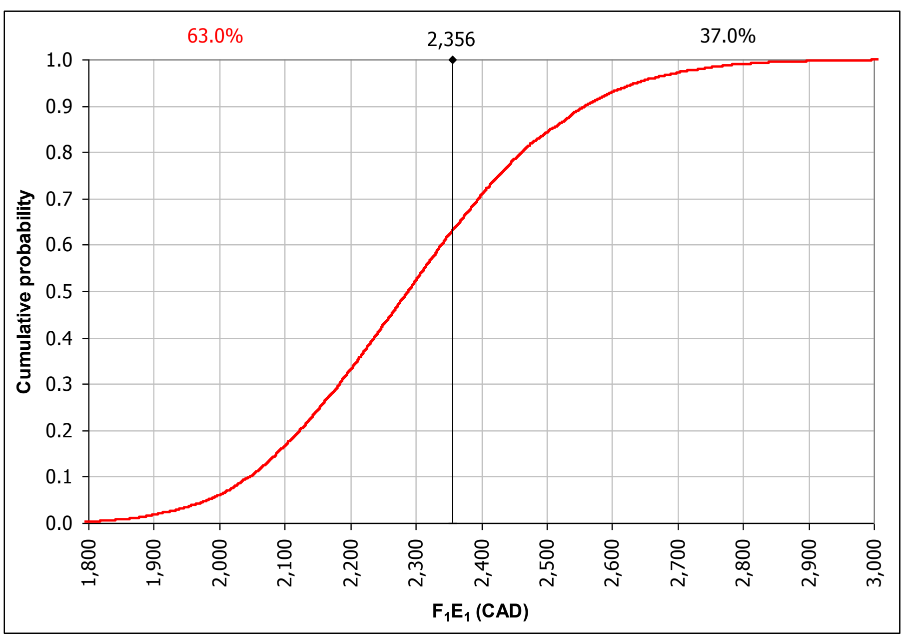

Figure 6.7 Cumulative probability distribution of F_1E_1 in the extended model

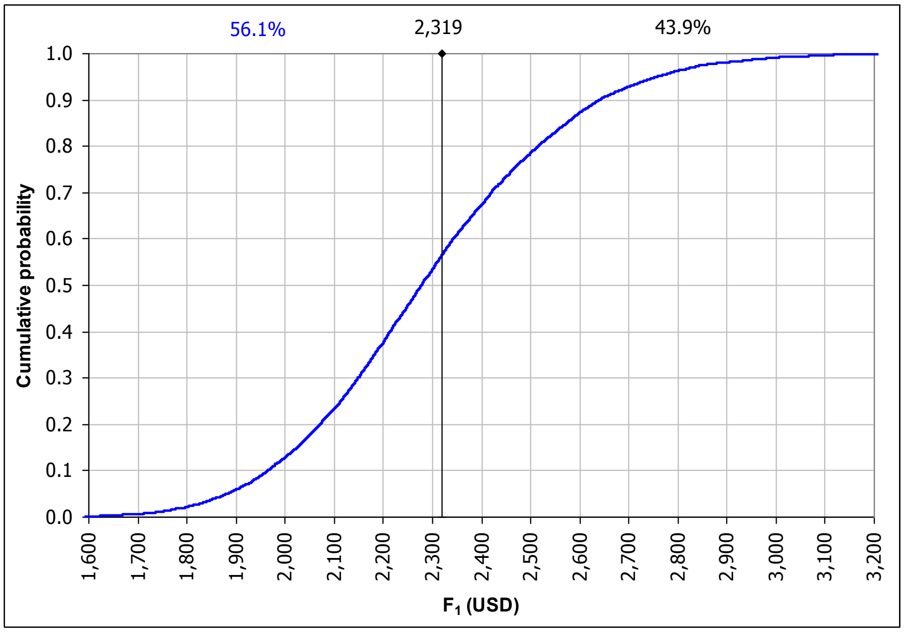

Figure 6.8 Cumulative probability distribution of F1 in the base model

6.3.2 Impact of risk aversion level on optimal hedging against exchange rate risk

The results in Table 6.2 show that when the exchange rate volatility increases, the supply chain exploits the opportunity associated with the expected decrease in aluminum price by buying more aluminum at t_1. However, this increase in Q_{a1} results in an increase in the holding cost of aluminum sheets. To balance this increase, the supply chain decreases the quantities of beer shipped to the distribution center, which, in turn, increases the stockout cost. The net change in the expected total opportunity cost is, however, significant only when the volatility increases by a ratio of 1.8. Purchasing large quantities of aluminum at t_1 results in large excess quantities carried over throughout the demand period considered in the model, and then to the next planning period. This decision may not be feasible for a more risk averse supply chain that cannot accept high inventory carrying costs, especially under high demand uncertainty. To investigate the impact of the risk aversion level on the model results we incorporate the exchange rate risk into the integrated base model in which VAR = 1.5, SDD = 4.5, APV = B. We created a set of treatments for the different exchange rate volatility ratios. The optimization results are summarized in Table 6.3.

Table 6.3 Optimization results of extended model with VaR = 1.5

	VAR = 1.5, SDD = 4.5, APV = B						
	CAD/USD exchange rate volatility ratio						
	1.0	1.10	1.20	1.30	1.40	1.60	1.80
E(TOC)	580,769	564,297	562,391	542,881	471,331	467,959	460,534
SD	690,156	683,397	684,247	687,275	734,255	719,916	720,325
Q_{a0}	11.4	13.1	13.1	8.9	0.0	0.0	0.0
Q_{a1}	177.7	176.7	177.0	179.6	187.8	178.0	183.0
Q_a	189.1	189.8	190.1	188.5	187.8	178.0	183.0
N_p	200	142	178	0	0	0	0
N_c	1,118	616	610	586	0	0	0

A comparison between the results in Tables 6.2 and 6.3 sheds light on the impact of the risk aversion level on the strategies of hedging the exchange rate risk, and on the performance of the supply chain. As expected, a more risk averse supply chain (VaR = 1.5) uses a smaller aluminum quantity in all the treatments except for the case when the volatility ratio is 1. In this latter case the supply chain uses a slightly higher Q_a but also hedges against increases in the aluminum price by purchasing Q_{a0} units of aluminum and N_c call options at t_0 that were not used by the less risk averse supply chain. Hedging using Q_{a0} and N_c is used in the treatments corresponding to exchange rate volatility ratios of 1.0 to 1.3. It is only when the volatility ratio is higher than 1.3 that all of the aluminum quantity is purchased at t_1 and no financial hedging tool is used. As for the expected opportunity cost, the decrease in E(TOC) as volatility increases is found to be statistically significant when the volatility ratio increases from 1.0 to 1.1, from 1.2 to 1.3, and from 1.3 to 1.4.

Figure 6.9 illustrates a graphical comparison of the results presented in Tables 6.2 and 6.3. As the exchange rate volatility changes, the change in the expected opportunity cost is depicted by the solid lines and the change in the total aluminum quantity purchased is depicted by the dashed lines. The square marks tag the performance of the more risk averse supply chain (VaR = 1.5) at the respective exchange rate volatility, and the triangular marks tag the performance of the less risk averse supply chain (VaR = 1.8) at these volatilities.

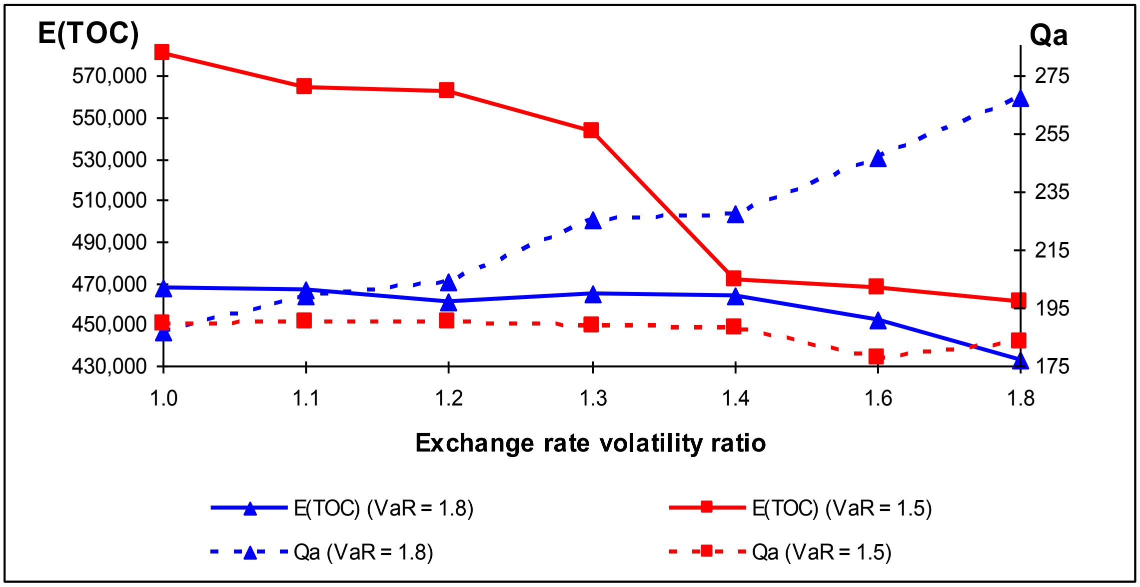

Figure 6.9 Exchange rate volatility effects on E(TOC) and Q_a in base and extended models

6.3.3 Model performance with and without hedging exchange rate risk

In order to evaluate the benefits of hedging the exchange rate risk, we compare the performance of a supply chain in two cases. In both cases the supply chain is exposed to exchange rate risk, but it hedges this risk only in one case. In the second case the supply chain retains the risk, that is, the exchange rate risk is unhedged. While the first case is captured by the extended model discussed above, the second case is modeled as described below.

6.3.3.1 Performance of a supply chain with unhedged exchange rate risk

To study the performance of a supply chain that does not hedge its exchange rate risk, we denominate all the components of E(TOC) optimized in the base model in CAD. For most of these cost components, the calculations used to denominate them in CAD are based on simply replacing the USD values of the aluminum spot price by values converted into CAD (CAD S = USD S x E in CAD/USD) in the corresponding formulations. The only cost components that require a different approach are the payoffs from the call and put options. For these two components, the conversion calculations are based on the following procedure that describes the series of transactions made by the supply chain to hedge aluminum price risk using call options. At t_0, the supply chain buys a number, N_c, of European call options on aluminum futures (traded in USD) with a strike price equal to USD K (equals to USD F_0) for a premium equal to USD c. The supply chain buys an amount of USD equal to cN_c for a price of CAD cN_cE_1. At t_1, the futures price changes from USD F_0 to USD F_1 and the CAD/USD exchange rate changes from E_0 to E_1. When $F_1 > F_0$ the options payoff is USD $N_c(F_1 – K)$. The supply chain sells this USD amount for an equivalent CAD amount using the exchange rate of E_1. A similar procedure applies for the put options. The results of the models with unhedged exchange rate risk are presented in Table 6.4.

Table 6.4 Optimization results of model with unhedged exchange rate risk

	VAR = 1.8, SDD = 4.5, APV = B					VAR = 1.5, SDD = 4.5, APV = B				
	CAD/USD exchange rate volatility ratio					CAD/USD exchange rate volatility ratio				
	1.00	1.10	1.20	1.30	1.40	1.00	1.10	1.20	1.30	1.40
E(TOC)	573,557	571,005	568,460	565,911	563,359	725,667	724,720	723,766	722,809	721,850
SD	909,476	903,181	897,106	891,228	885,549	631,866	630,361	628,942	627,602	626,643

6.3.3.2 Performance of a supply chain that hedges exchange rate risk

The performance of a supply chain that hedges exchange rate risk is examined in the results of the extended model. However, the results in Tables 6.2 and 6.3 show that in the presence of exchange rate risk in the extended model, the total aluminum quantity purchased is much higher than that in the base model, especially in the treatments with VAR = 1.8. To better compare the performances of the base model (unhedged exchange rate risk) and extended model (hedged exchange rate risk), we eliminate the effects of purchasing a larger quantity of aluminum by adding a constraint to the extended model treatment with an exchange rate volatility ratio of 1.0. This constraint limits the total aluminum quantity to a maximum level equal to that optimized in the base model (177.8 million cans for VAR = 1.8 and 178.0 million cans for VAR = 1.5). The optimal value of Q_a is found to be 177.1 and 177.7 million cans for VAR = 1.8 and VAR = 1.5, respectively. For all the other treatments with an exchange rate volatility ratio higher than 1.0, we added a constraint setting Q_a to be equal to the optimized value in the treatment with a volatility ratio of 1.0. The optimization results are summarized in Table 6.5.

Table 6.5 Optimization results of extended model with Q_a constrained to be less than or equal to an upper value

	VAR = 1.8, SDD = 4.5, APV = B					VAR = 1.5, SDD = 4.5, APV = B				
	CAD/USD exchange rate volatility ratio					CAD/USD exchange rate volatility ratio				
	1.00	1.10	1.20	1.30	1.40	1.00	1.10	1.20	1.30	1.40
E(TOC)	495,182	493,189	490,290	493,200	491,055	595,937	583,165	568,255	557,776	537,629
SD	863,254	879,361	893,778	778,668	771,866	677,700	687,217	690,760	700,840	700,907
Q_{a0}	0.0	0.0	0.0	0.0	0.0	19.8	17.1	13.8	1.7	0.6
Q_{a1}	177.1	177.1	177.1	177.1	177.1	157.9	160.6	163.9	176.0	177.1
Q_a	177.1	177.1	177.1	177.1	177.1	177.7	177.7	177.7	177.7	177.7
N_p	939	1,324	1,749	0	0	47	166	60	106	4
N_c	0	0	0	0	0	330	315	309	928	674

6.3.3.3 Effects of exchange rate hedging at different risk aversion levels and exchange rate volatilities

As expected, comparing E(TOC) values between Tables 6.4 and 6.5 shows that a supply chain that does not hedge exchange rate risk incurs a higher expected opportunity cost than a supply chain that hedges this risk. However, this difference in E(TOC) between these two supply chains is also a function of the risk level that the supply chains are willing to assume and the exchange rate volatility. For example, when the exchange rate volatility ratio is 1 the difference in E(TOC) between the hedged and unhedged cases is 13.7% when VaR is 1.8, while this difference is 17.9% when VaR is 1.5. On the other hand, when VaR is 1.5 the difference in E(TOC) between the hedged and the unhedged cases is 17.9% when the exchange rate ratio is 1, while this difference is 19.5% when the volatility ratio is 1.1.

Figure 6.10 depicts the percentage difference in E(TOC) between a supply chain that does not hedge its foreign exchange risk and one that hedges it (Unhedged versus Hedged). The upper line illustrates an increase in the difference in E(TOC) when these supply chains are more risk averse (VaR = 1.5). The lower line illustrates minor changes in the difference in E(TOC) when these supply chains are less risk averse (VaR = 1.8). The gap between the two lines reveals the impact of the risk aversion level on the difference in E(TOC). For the same exchange rate volatility, the difference in E(TOC) between the hedged and unhedged cases when VaR = 1.5 is higher than that when VaR = 1.8. Moreover, the positive slope of the upper line indicates an influence of the exchange rate volatility on the difference in E(TOC) in the cases when VaR = 1.5. This influence is negligible in the cases when VaR = 1.8, as illustrated by the very mild slopes in the lower line.

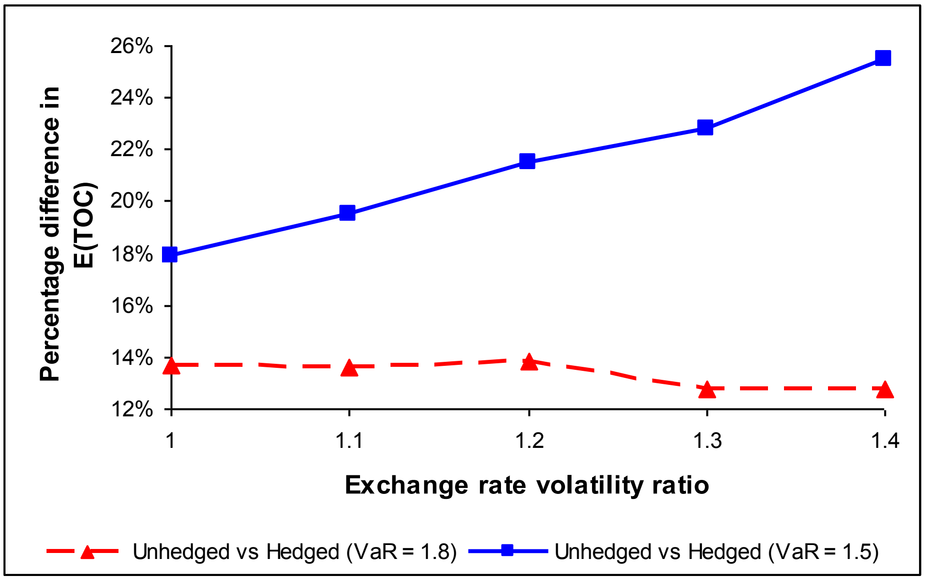

Figure 6.10 Comparing effects on E(TOC) of hedging exchange rate risk at two risk aversion levels

6.3.3.4 Effects of risk aversion level at different exchange rate hedging strategies and volatilities

Similar to the findings in the base model, comparing E(TOC) values between the right and left sides in each of Tables 6.4 and 6.5 show that a more risk averse supply chain incurs a higher expected opportunity cost than a less risk averse supply chain. However, the difference in E(TOC) between these two levels of risk aversion is also a function of the supply chain strategy in hedging the exchange rate risk and the volatility of this exchange rate. For example, when the exchange rate volatility ratio is 1 the difference in E(TOC) between the two levels of risk aversion is 16.9% when the supply chain hedges the exchange rate risk, while this difference is 21.0% when the supply chain does not hedge this risk. On the other hand, when the supply chain does not hedge the exchange rate risk the difference in E(TOC) between the two risk aversion levels is 16.9% when the exchange rate volatility ratio is 1, while this difference is 13.7% when the volatility ratio is 1.2.

Figure 6.11 depicts the percentage difference in E(TOC) between more risk averse and less risk averse supply chains (VaR 1.5 versus VaR 1.8). The upper line illustrates a mild increase in this difference in E(TOC) when these supply chains do not hedge foreign exchange risk. The lower line illustrates a decrease in the difference in E(TOC) when these supply chains hedge foreign exchange risk. The gap between the two lines reveals the impact of the hedging strategy on the difference in E(TOC). For the same exchange rate volatility, the difference in E(TOC) when the supply chains do not hedge foreign exchange risk is higher than that when they do hedge. Moreover, the negative slope of the lower line indicates an influence of the exchange rate volatility on the difference in E(TOC) in the cases when the supply chains hedge foreign exchange risk. As this volatility increases, the percentage difference in E(TOC) decreases. This influence is negligible when the supply chains do not hedge, as illustrated by the very mild slopes in the upper line.

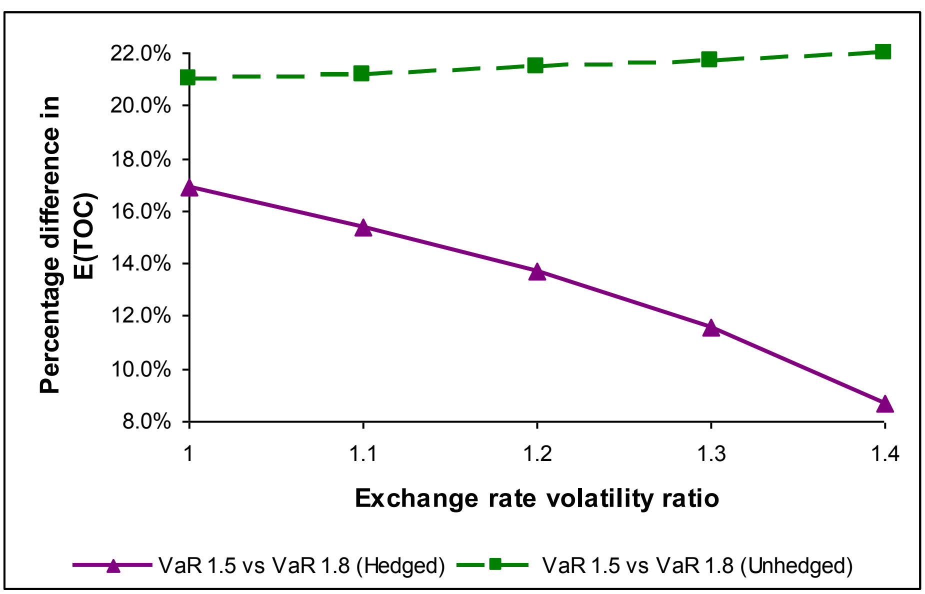

Figure 6.11 Comparing effects of risk aversion level on E(TOC) in hedged & unhedged cases

6.4 Conclusion and managerial insights

In this Chapter, we study the performance of an international supply chain that is exposed to exchange rate risk, in addition to fluctuation in aluminum prices and demand uncertainty. We extend our base integrated model by incorporating the exchange rate in the calculation of the expected opportunity cost and in using financial options on an index which consists of the product of the aluminum futures price denominated in USD and the CAD/USD exchange rate.

We implement the model extension on the integrated model, setting the three factors at their base level. We generate a set of treatments in which the exchange rate volatility changes by a ratio ranging from 1.0 to 1.8. We find the optimal solutions in these treatments. The results reveal that in the presence of exchange rate risk, the supply chain does not hedge the aluminum price increase with inventory procured at t_0 as was the case in the base model. This is due to a lower probability of an opportunity profit resulting from hedging with Q_{a0}. The numbers of put and call options are also found to decrease in the extended model, due to lower probability of positive payoff. On the other hand, the quantity purchased at t_1 is higher in the extended model and it increases as the exchange rate volatility ratio increases. The increase in Q_{a1} exploits the high probability of decrease in the aluminum price, but results in an increase in the holding cost. According to the results, only when the volatility ratio is 1.8, the increase in Q_{a1} would yield a significant decline in the expected opportunity cost.

To verify the feasibility of buying an excess aluminum quantity at t_1 when the supply chain is more risk averse, we incorporate exchange rate risk in the treatment in which the risk aversion level is higher and the other two factors are kept at their base level. The results show that, contrary to the cases of lower risk aversion level, as the exchange rate volatility increases the aluminum quantity does not change and the expected opportunity cost exhibits more significant declines. As the exchange rate volatility increases, a less risk averse supply chain tends to buy more aluminum and the expected opportunity cost is almost constant. On the other hand, a more risk averse supply chain buys almost the same quantity of aluminum and the expected opportunity cost declines as the exchange rate volatility increases. Moreover, the more risk averse supply chain keeps using operational hedging when the exchange rate volatility ratio is less than 1.4.

To study the benefits of hedging exchange rate risk, we compare the performance of a supply chain, which is exposed to exchange rate risk, in two cases. In one case the supply chain hedges this risk and in the other case it does not.. As expected, a supply chain that hedges exchange rate risk performs better than a supply chain that does not hedge this risk. However, the difference in the two performances is found also to be function of the risk aversion level and the exchange rate volatility. In the case of a higher risk aversion level, the improvement in performance increases as the volatility increases, while it is the same in the case of lower risk aversion level. At any volatility ratio, the improvement in the former case is higher than the improvement in the latter case. A more risk averse supply chain achieves higher improvements in its performance when it hedges foreign exchange risk than a less risk averse supply chain. In the former case, the improvement rate significantly increases as the exchange rate volatility increases while it is almost constant in the latter.

In line with the findings in the base model, a higher risk aversion level increases the opportunity cost. However, this relationship is also a function of the hedging position and the exchange rate volatility. In the case when the supply chain hedges exchange rate risk, the increase in opportunity cost declines as the exchange rate volatility increases, while it is the same in the case when the supply chain does not hedge the exchange rate risk. At any volatility ratio, the opportunity cost increase in the former case is higher than the increase in the latter case. A supply chain that hedges exchange rate risk incurs less loss at a higher risk aversion level than a supply chain that does not hedge. In the former case, the loss rate significantly decreases as the exchange rate volatility increases while it is almost constant in the latter.

Appendix C - Simulating the Spot Price, Futures Price and the Foreign Currency Exchange Rate

Assuming that aluminum spot prices, futures prices and currency exchange rates are lognormally distributed, we simulate values for these variables at the future time t_1, which coincides with the options' expiration date, according to the procedure presented in Hull (2006). Thus,

$$S_1 = S_0 \times \exp\left[\left(\mu_1 - \frac{\sigma_1^2}{2}\right)T + \sigma_1\sqrt{T}\varepsilon_1\right] \tag{C1}$$

$$F_1 = F_0 \times \exp\left[\left(\mu_2 - \frac{\sigma_2^2}{2}\right)T + \sigma_2\sqrt{T}\varepsilon_2\right] \tag{C2}$$

$$E_1 = E_0 \times \exp\left[\left(\mu_3 - \frac{\sigma_3^2}{2}\right)T + \sigma_3\sqrt{T}\varepsilon_3\right] \tag{C3}$$

where S_0, F_0 and E_0 are the spot price, futures price and currency exchange rate, respectively, at the current time t_0; μ_1, μ_2 and μ_3 are the annualized mean of the continuously compounded returns on the spot price, on the futures price and on the currency exchange rate, respectively; and σ_1, σ_2 and σ_3 are the annualized standard deviations of the continuously compounded returns on the spot price, on the futures price and on the currency exchange rate, respectively. μ_1, μ_2, σ_1 and σ_2 are estimated using historical daily data on spot and futures prices obtained from Bloomberg for a 12 week period in which the last date coincides with the date just prior to the options' purchase date. μ_3 and σ_3 are estimated using historical daily data on currency exchange rates obtained from Datastream for a 12 week period in which the last date coincides with the date just prior to the options' purchase date. T is the time (in years) to the options' expiration dates. ε_1, ε_2 and ε_3 represent standard normal random variables among with correlations ρ_{12} (between the returns on the spot and on the futures), ρ_{13} (between the returns on the spot and on the exchange rate), and ρ_{23} (between the returns on the futures and on the exchange rate). These correlations are estimated from the same historical data used to estimate the mean and standard deviations of the continuously compounded returns on the spot, futures and currency exchange rate.

ε_1, ε_2 and ε_3 are simulated as follows:

$$\varepsilon_1 = \alpha_{11}x_1,\ x_1 \sim \Phi(0,1) \tag{C4}$$

$$\varepsilon_2 = \alpha_{21}x_1 + \alpha_{22}x_2,\ x_2 \sim \Phi(0,1) \tag{C5}$$

$$\varepsilon_3 = \alpha_{31}x_1 + \alpha_{32}x_2 + \alpha_{33}x_3,\ x_3 \sim \Phi(0,1) \tag{C6}$$

where

$$\alpha_{11} =$$

$$\alpha_{21} = \rho_{12};\ \alpha_{22} = \sqrt{1-\rho_{12}^2} \tag{C7}$$

$$\alpha_{31} = \rho_{13};\ \alpha_{32} = \frac{\rho_{23}-\rho_{13}\rho_{12}}{\sqrt{1-\rho_{12}^2}};\ \alpha_{23} = \sqrt{1-\rho_{13}^2-\frac{(\rho_{23}-\rho_{13}\rho_{12})^2}{1-\rho_{12}^2}}$$

where x_1, x_2 and x_3 represent independent standard normal random variables.

Chapter 7

Conclusion

7.1 Overall Results and Discussions

Our literature survey had revealed shortages in systematic methods for risk identification and for selection of risk management tools. To identify risks, we proposed the use of three different constructs. We associated a specific adverse event to a source of risk that emanates from a risk domain. We recognized four risk domains: internal operations, external stakeholders, marketplace and environment. To support the decision of selecting the appropriate risk management method, we classified these methods into three categories: avoidance, prevention and mitigation approaches. These two classifications represent the main building blocks of our supply chain risk management framework. On the basis of this framework, we designed a planning process that can be used by practitioners in the context of a risk management strategy.

The literature review also revealed a shortage in papers integrating operational and financial approaches. We summarized the reviewed papers in Table 3.5. In almost all these papers, exchange rate risk is addressed. Eventually, the financial instruments that are most commonly used are currency derivatives. As for the operational methods, the most common approaches are geographic dispersion, switching production and capacity allocation. Our research is different from the reviewed papers in terms of the type of risk and the selection of the risk management approach. In our model, we incorporated commodity price risk, in terms of aluminum price fluctuation, and we hedged this risk with inventory management and options on aluminum futures.

The risk management strategy incorporated in our base model is developed according to our SCRM framework. Figure 7.1 depicts the planning process that underlies this strategy. The supply chain is exposed to demand uncertainty and aluminum price fluctuation. Although some avoidance and prevention approaches can be deployed to manage these two risks, these are not in the scope of our research. To explore the benefits of integrating operational and financial methods, we develop a mitigation plan that involves an integrated approach. Under uncertain demand conditions, the supply chain decides on levels of beer inventory to maintain in the distribution center in order to minimize stockout and holding costs. The flow quantities of beer and empty cans along the supply chain are decided accordingly. To feed these flows, aluminum sheets need to be procured at an earlier time. The procurement price is a major determinant of packaging cost. Under a fluctuating aluminum price, the supply chain mitigates an increase in the packaging cost by hedging the price with a quantity of aluminum sheets and a number of call options. In case of a decline in the price, the supply chain would be at a disadvantage due to the quantity purchased at the higher price. To offset this opportunity cost, a number of put options are purchased. The supply chain evaluates its risk management performance in terms of the total expected opportunity cost.

The quantitative part of our research is presented in three chapters. In Chapter 4, we discussed the supply chain problem and explained the base model that integrates operational and financial approaches to manage risks emanating from aluminum price fluctuation and demand uncertainty. The supply chain hedges the aluminum price with inventory and options on aluminum futures. Demand uncertainty is managed by a coordinated inventory system across the supply chain. The inventory and financial decisions are made simultaneously in the integrated model. In the sequential model, the two decisions are made separately. The two models were solved with simulation-based optimization and results were compared to draw conclusions on the advantages of integrated approach over the other. Furthermore, experimental design was used to study the impact of three factors on the model performance. These factors are risk aversion level, aluminum price volatility and demand variability. Each factor was represented at three levels.

The supply chain risk management performance was evaluated in terms of the total expected opportunity cost. This performance was found to vary with the change of the business environment, which is defined by the levels of the aforementioned three factors. Results showed that the supply chain can significantly reduce the opportunity cost by adopting the integrated model rather than the sequential model. This reduction ranges from 5% to 10% depending on the business environment in which the supply chain operates. The reduction ranges from \$ 25,000 to \$ 65,000 over the eight week demand period. On the other hand, the improvement obtained with the integrated approach was found not to be significant in a number of cases, notably when a more risk averse supply chain operates under low demand uncertainty. The same was observed when a less risk averse supply chain operates under high demand uncertainty. This observation is very important and needs to be considered while setting the supply chain risk management strategy. Implementing the integrated model requires close collaboration among supply chain partners and between functions within each firm. As this collaboration can be very costly, a supply chain that operates under a business environment in which the integrated approach is not beneficial would opt not to establish such collaboration

Other than the difference in their opportunity costs, the integrated and sequential models are distinguished by their respective levels of operational hedging strategy. Operational hedging is implemented through the purchase at time t_0 of a portion of the aluminum sheets that would be later needed when production starts at time t_1. We measured the extent of operational hedging by the ratio, u_0, of the quantity purchased at t_0 over the total quantity. According to the results, a supply chain adopting the sequential model would use more operational hedging than a supply chain adopting the integrated model. In both models, however, a more risk averse supply chain uses more operational hedging and the degree of this hedging increases when demand variability increases. Under such a business environment, the ratio u_0 is at a maximum of 45% in the sequential model.

The impacts of the three factors and their interaction effects on the models can be inferred from the overall results. However, deductions would be limited to the discrete values of the factors' levels. To gain insights on the model performance as the values of the factors vary on continuous scale, within the range of the three levels of each factor, a quadratic regression model was developed. This model explained the variations of the expected opportunity cost and revealed significant interaction effects among the factors on this cost. Visual illustrations of these interactions are depicted in Figures 3.3. - 3.5. Important managerial insights were drawn from the regression model results. For example, in contrast to the inference made from the negative correlation between the risk aversion level and the opportunity cost, results from the regression model revealed that the opportunity cost stops declining when the risk aversion level reaches a threshold level.

Chapter 5 presents the first extension to our base model. In this extended model, we incorporated variability in the lead time duration to supply aluminum cans to the brewery. We modified the formulation of the base model accordingly. We used the same research methodology as in the base model with two changes: i) lead time variability was added to the three factors involved in the base model and ii) each factor was represented at only two levels in the experiments. We underlined two aspects pertinent to the inclusion of lead time variability in the model. First, with lead time variability, the product flow across the supply chain is different from the flow in the base model. In the latter, the total flow of aluminum sheets, empty cans and beer is identical in volume. In the extended model, the flow of aluminum sheets and cans is larger than the flow of beer. Second, lead time variability has significant interaction effects on the expected opportunity cost with the other factors. For example, the regression analysis results reveal that an increase in lead time variability would amplify (diminish) the effects of risk aversion level (demand uncertainty) on the expected opportunity cost. Important managerial insights can be drawn from these observations. If an increase in lead time variability is inevitable, then the supply chain can balance the ensuing increase in opportunity cost by being less risk averse. Other interaction effects and managerial insights are discussed in more detail in Chapter 5.

In the second extension of the base model (Chapter 6) we incorporated foreign exchange rate risk. The aim of this extended model is to examine the performance of an international supply chain, which is the case for most supply chains today. In our model, the brewery and the distribution center operate in Canada, while the can supplier operates in the United States. The supply chain is thus exposed to fluctuation in the CAD/USD exchange rate. We optimized the expected opportunity cost in various treatments of the integrated model under two risk aversion levels and different exchange rate volatilities. We performed a parametric analysis of the results and came out with a number of observations that emphasize the effects of exchange rate risk. At a lower risk aversion level, as the exchange rate volatility increases, the supply chain tends to purchase more aluminum, but the expected opportunity cost does not exhibit significant change. On the contrary, at the higher risk aversion level, as the exchange rate volatility increases, the aluminum quantity purchased stayed constant and the expected opportunity cost significantly declines.

We produced another set of results for the same treatments after adding to the model formulation a constraint that limits the quantity of aluminum to the value optimized in the base model. We compared these results (case of hedged exchange rate) to the results of the base model, after denominating the opportunity cost in CAD (case of unhedged exchange rate). We find that the hedging effect on the opportunity cost is higher when the supply chain is more risk averse. In this latter case, the hedging benefits increase as the exchange rate volatility increases. This volatility has no influence on the hedging benefits when the supply chain is less risk averse. We also found that the positive effect of a lower risk aversion level on the opportunity cost diminishes when the supply chain hedges the exchange rate. In this latter case, the benefits of being less risk averse exhibit more reduction as the exchange rate volatility increases.

7.2 Areas for Future Research

In the future, our research can be expanded in different directions.

i) The operational and financial hedging decisions can be made through a dynamic process rather than making these decisions at a single fixed date. At the start of the process, the supply chain observes the aluminum price and based on the historical movement of this price it may decide to buy a quantity of aluminum sheets and a number of options on aluminum futures. After a specific time interval, taking into consideration the quantity of aluminum sheets on hand and the number of options it already holds, the supply chain evaluates new decisions. If the aluminum price has dropped, the supply chain may buy a second lot of aluminum sheets and a number of call options. On the other hand, if the aluminum price has increased, the supply chain buys only a number of put options. This process continues for a number of time intervals. The use of futures or forward contracts instead of options may be found to be more effective under this dynamic process.

ii) The supply chain can include multiple can suppliers. In our current research, we examined the case in which the brewery operates in Canada and procures cans from a foreign supplier operating in the U.S. If the brewery has another domestic supplier for the cans, the supply chain can then manage the exchange rate risk by switching the source of supply accordingly. To incorporate this option in our model, one has to come out with an appropriate estimation method for the switching cost. Moreover, suppliers' capacity constraints can also be incorporated.

iii) The demand involved in our model is assumed to be an aggregate demand for all brands of beer that the brewery produces. Major breweries have large varieties of beer brands with different demand characteristics. Including multiple brands in the model bring in new aspects that enrich the research. On one hand, correlations among demands for different brands would need to be determined. On the other hand, postponement of part of the process in which the cans are labeled would be part of the overall risk management strategy.

iv) One component of the expected total opportunity cost in our model is the stockout cost. The supply chain makes decisions that would minimize the total expected opportunity cost without specific consideration for the proportion of unsatisfied demand. However, such approach may not be feasible for firms with aggressive marketing plans. The model can be modified to keep the unsatisfied demand within certain limits. Such model expansion can be combined with the addition of multiple brands as discussed above. Demand for one brand can be shifted to another brand to avoid excessive stockouts.

v) In our model, we assumed a fixed selling price for the beer. The scope of the research can be expanded by considering this price as variable. For this case, the impact of pricing on demand would need to be considered.

vi) As suggested by recent studies in the area of modeling under uncertainty, we can improve the solutions obtained by using stochastic optimization routines in which the response surface based outcome becomes an input to stochastic programming.

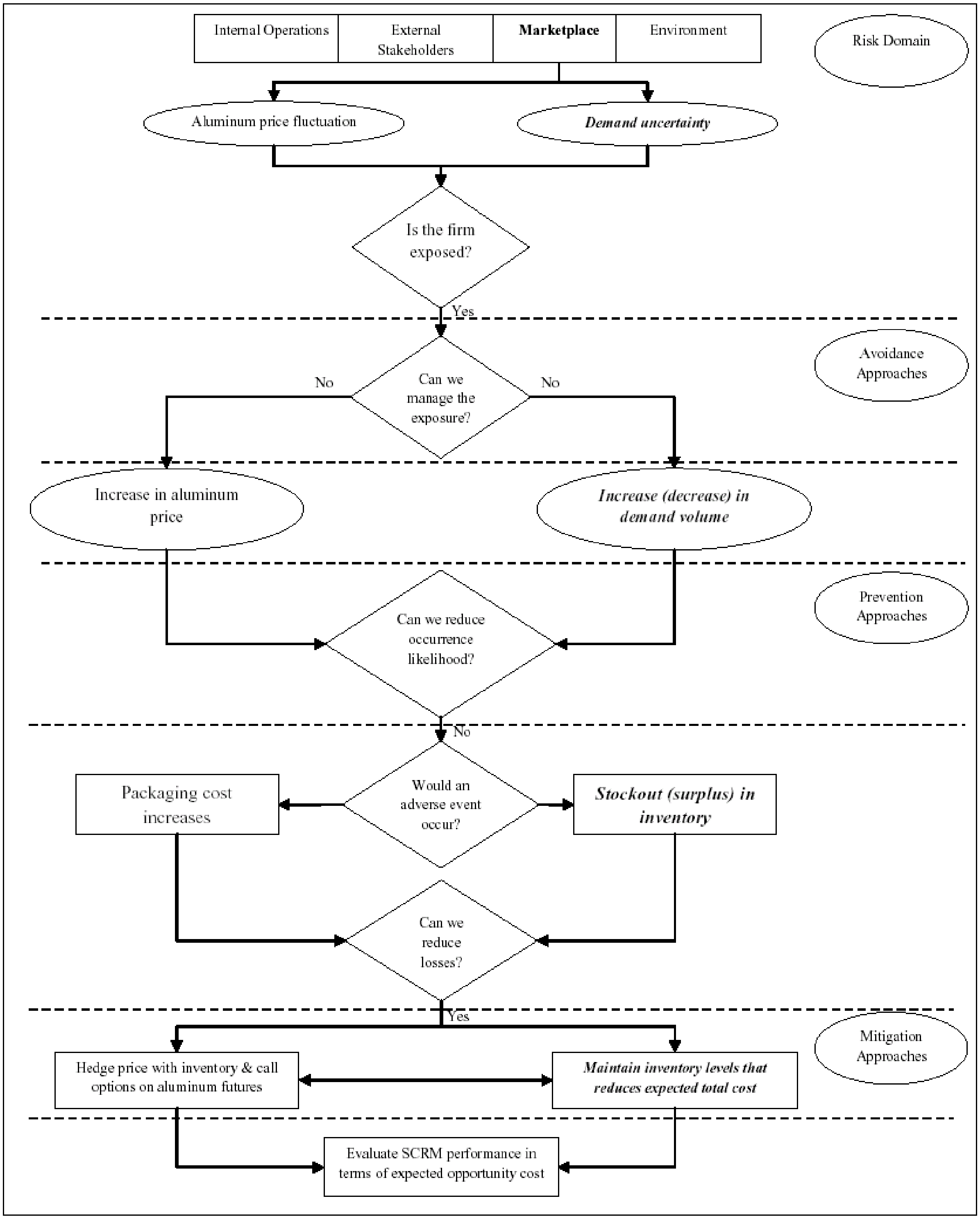

Figure 7.1 Planning process underlying our SCRM base model

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