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Supply chain risk management (SCRM) is an emerging field that generally lacks integrative approaches across different disciplines. This study contributes to narrowing this gap by developing an integrated approach to SCRM using operational methods and financial instruments. We study a supply chain composed of an aluminium can supplier, a brewery and a distributor. The supply chain is exposed to aluminium price fluctuation and beer demand uncertainty. A stochastic optimisation model is developed for managing operational and financial risks along the supply chain. Using this model as a base, we compare the performance of an integrated risk management model (under which operational and financial risk management decisions are made simultaneously) to a sequential model (under which the financial risk management decisions are made after the operational risk management decisions are finalised). Through simulation-based optimisation and using experimental designs and statistical analyses, we analyse the performance of the two models in minimising the expected total opportunity cost of the supply chain. We examine the supply chain performance as a function of three factors, each at three levels: risk aversion, demand variability and aluminium price volatility. We find that the integrated model outperforms the sequential model in most but not in all cases. Furthermore, while the results indicate that the supply chain improves its performance by being less risk averse, there exists a threshold beyond which accepting a higher risk level is not justified. Managerial insights are provided for various business scenarios experimented with.

Keywords: risk management; supply chain; finance; inventory; integrated methods; optimisation via simulation

1. Introduction

Risk management provides an important arena to visualise and understand the true nature of supply chain management and its interdisciplinary context. As corporate risk management spans several disciplines such as procurement, finance, operations and marketing, the approaches used to manage risks along a supply chain also need to be interdisciplinary. As reported in a survey by Bandaly et al. (2013), the literature is short on studies using interdisciplinary and integrated approaches to supply chain risk management (SCRM).

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

1.1 Conceptual background

1.1.1 Problem setting

A brewery purchases aluminium cans from a can supplier, produces canned beer and then transports it to a distribution centre which maintains an inventory to meet retailers’ demand. The supply chain faces risks which originate from both upstream and downstream. The can supplier faces aluminium price volatility (APV), while the distribution centre faces uncertainty in beer demand. APV causes fluctuations in packaging cost, while beer demand uncertainty causes either a

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shortage or a surplus in finished goods inventory. Our integrated model aims to capture the benefits of integrating operational methods and financial instruments in managing these risks.

1.1.2 Model framework
The model assumes a partnership-like relationship among the members of the supply chain. In this vein, we assume that the demand information at various stages across the supply chain is not distorted and that it flows in a timely manner across the supply chain.

The model incorporates inventory levels of three items: canned beer at the distribution centre, empty aluminium cans at the brewery and aluminium sheets at the can supplier. While the inventories of aluminium sheets and canned beer are physically maintained and managed solely by the can supplier and the distribution centre, respectively, the inventory of empty aluminium 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 minimises the expected total opportunity cost, \( E(\text{TOC}) \), of the supply chain as a whole. The total opportunity cost includes: (i) inventory carrying costs at all stages of the supply chain, stockout costs due to unsatisfied demand for beer, and (ii) costs associated with hedging APV and aluminium demand uncertainty with inventory and with options on aluminium futures. Our model builds on the premise that the decisions on aluminium and canned beer inventories need to be made in an integrated manner to minimise 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.

1.2 Literature review
Due to the limitations inherent in the application of individual approaches, research on integrated operational and financial approaches to manage risk has attracted more interest from researchers and practitioners more recently. Triantis (2000) notes that 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. Servaes, Tamayo, and Tufano (2009) report that 63% of companies participating in a survey recognise the benefits of enterprise risk management. Previous studies such as those of Miller (1992) and Carter, Pantzalis, and Simkins (2001) conclude that managing risk on a firm level is more effective than managing risk on a functional level. Companies may even incur losses when individual functional divisions attempt to implement risk management approaches in isolation from other divisions. 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, Scharfstein, and Stein 1994). In their review of operational, financial and integrated models, Bandaly et al. (2013) report that the findings of a number of models which integrate operational and financial approaches support the above arguments. In what follows, we review theoretical models as well as empirical studies of integrated operational and financial approaches.

1.2.1 Theoretical models
The real options approach provides operational flexibility by allowing the firm to switch production between plants located in different countries to supply different markets (Huchzermeier and Cohen 1996; Kogut and Kulatilaka 1994). Just as currency options do, this 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, Parsons, and Triantis (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, Parsons, and Triantis (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, Dong, and Kouvelis (2007) assume that production capacity is limited and that the real option available to the firm is to postpone capacity allocation. Upon the realisation 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 maximise the firm’s expected profit and minimise 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, Rudi, and Van Mieghem (2010) use financial tools to hedge against demand uncertainty. These authors examine the relationship between financial risk management 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 realised. These authors show that while postponement flexibility is a substitute for financial risk management, product choice can be either a complement or a substitute for financial risk management, depending on the nature of the correlation between the demands for the different 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 maximise expected profit and minimise its variance.

1.2.2 Empirical studies

Some empirical studies shed light on the benefits of integrating operational and financial risk management strategies. In their studies of multinational and non-financial firms, Allayannis, Ihrig, and Weston (2001), Kim, Mathur, and Nam (2006) and Carter, Pantzalis, and Simkins (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 foreign exchange risk. Other operational hedging strategies include the real options approach 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.

Exchange rate risk is addressed in almost all of the above-reviewed papers. The financial instruments that are most commonly used to manage exchange rate risk are currency derivatives. The most common operational risk management approaches are geographic dispersion, switching production and capacity allocation.

1.2.3 Contribution of our paper

Our study differs from the above-reviewed papers on the types of risks which are addressed as well as on the selection of the risk management approach. In our model, we incorporated demand uncertainty, in the form of uncertainty in the demand for beer, which leads to uncertainty in the demand for aluminium cans and aluminium, as well as commodity price risk, in terms of aluminium price fluctuation, and we manage these risks using inventory as well as options on aluminium futures. Another aspect that distinguishes our paper is the inclusion of the upstream side of the supply chain. In our model, the inventory levels maintained by the can supplier are determined in coordination with the brewery and the distribution centre.

Section 2 describes the integrated risk management model in detail. We also discuss a sequential model which first applies operational risk management methods to determine the optimal purchase quantities of the input commodity (aluminium) and inventory levels maintained by the different members of the supply chain, and then apply financial risk management methods by determining the optimal purchase quantity of call and put options on aluminium futures contracts. Section 3 presents the experimental design used for the simulation-based optimisation. Section 4 discusses the results. These reveal that, in most of the cases addressed, the integrated model outperforms the sequential model in minimising the expected total opportunity cost. Section 5 presents conclusions and offers areas for further research.

2. The model developed

2.1 Supply chain risk management process

Figure 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
\[ i = \{ a, b, c \} \text{ denotes aluminium sheets, canned beer and empty cans, respectively, and } j = \{ 0, 1, \ldots, 13 \} \text{ represents a point in time.} \]

2.1.1 Risk management using inventory and options on aluminium futures

Time \( t_0 \) represents the current point in time at which the can supplier places an order for aluminium 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 \( L \) required by the can supplier to produce empty cans (4 weeks) and the lead time \( L_0 \) required by the brewery to produce beer (1 week). Faced with aluminium price variability and an uncertain demand for beer, the supply chain needs to make two strategic decisions on: (i) the quantity of aluminium sheets to procure \( (Q_i) \) and (ii) the effective price to pay for the aluminium. The can supplier and the brewery make their decisions based on their mutual objective of optimising the supply chain performance, defined as the minimisation 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 aluminium \( Q_{a0} \) from the spot market at the spot price of \( S_0 \) per unit. This purchase is a hedge against future increases in the aluminium price. At time \( t_1 \), the can supplier purchases a second quantity of aluminium \( Q_{a1} \) from the spot market at a spot price \( S_1 \). The purchase of aluminium in two batches reduces the total holding costs associated with holding aluminium 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 aluminium purchased at \( t_0 \), if the aluminium price were to decline in the future, then the supply chain would incur an opportunity cost, since by waiting to purchase aluminium, it could have done so at a lower price. To offset the opportunity cost associated with aluminium price decreases, the can supplier buys at \( t_0 \) a number \( N_p \) of European put options on aluminium 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 so that the exercise price \( K \) is equal to the underlying aluminium 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 aluminium 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 aluminium is given by \( Q_{a0}(S_0 - S_1e^{-rT_0}) \), 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 aluminium. However, if \( S_1 \) is greater than \( S_0 \), the initial purchase of aluminium 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 aluminium sheets \( (Q_{a1}) \) purchased at time \( t_1 \), the supply chain would incur an opportunity cost should the aluminium price increase. To offset this latter cost, at \( t_0 \), the supplier buys a number \( N_c \) of European call options on aluminium 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 aluminium quantity purchase \( Q_{a1} \) to \( t_1 \), an opportunity cost is incurred if the aluminium spot price \( S_1 \) is higher than its initial value \( S_0 \). This cost is given by \( Q_{a1}(S_1e^{-rT_0} - S_0) \). 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 aluminium purchase. On the other hand, if the aluminium...
spot price $S_t$ decreases below its initial value $S_0$, the decision to postpone the purchase of a quantity of aluminium to $t_1$ results in an opportunity gain. In this case, the call options will be left unexercised.

2.1.2 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 maximise the fill rate while minimising 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 (first demand period in our planning horizon). The same applies to all other weekly demands. The brewery estimates the demand $d_t$ that would be realised over week $w_t$ and accordingly ships a quantity of beer $Q_{b6}$ to the distribution centre 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 $P_{c5}$ at time $t_5 = t_b - L_b$. Empty cans are transferred from the warehouse in which a beginning inventory level of empty cans $B_{e5}$ is replenished by an incoming quantity of empty cans $Q_{e5}$ from the can supplier. After transferring $Q_{e5}$ 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 $Q_{e5}$ 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 aluminium sheets required to produce $P_{c1}$ is transferred from the beginning aluminium sheets inventory $B_{c1}$ at the can supplier, which equals the sum of the aluminium quantities purchased at $t_0$ and $t_1$. Following the transfer, an inventory level $E_{c1}$ remains on hand at the can supplier ready to be used during the following weeks.

At the start of week $j$, as the demand for canned beer $d_j$ starts being realised, the distribution centre satisfies this demand from available inventory $B_{b}$ ending up with remaining inventory $E_{b}$. The total quantity of canned beer distributed during the week is $M_{b}$. If $B_{b} < d_{j}$, the supply chain incurs a stockout cost ($s$). On the other hand, if $B_{b} > d_{j}$ 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 aluminium sheets. Subject to associated lead times, beer inventory is to be kept to a minimum level, while inventories of unprocessed aluminium sheets and empty cans are used 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. Thus, the decision-making is envisaged to involve a collaborative process among the can supplier, the brewery and the distributor. As such, it differs from the vendor managed inventory system for which the benefits are well documented in the literature (among others, Bookbinder, Gümüs, and Jewkes 2010; Kannan et al. 2013).

2.2 Integrated risk management model
The integrated risk management model solves for the decision variables $(Q_{a0}, Q_{a1}, N_c, N_p, Q_{e0}$ and $Q_{e5})$ in order to minimise 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).

2.2.1 Assumptions
We consider an aggregate demand for beer across multiple brands from which the requirement for aluminium 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 centre 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 aluminium 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.
2.2.2 Decisions and costs in the first time span \((T_0)\)

The decision variables in the first time span, \(T_0\), are the quantities of aluminium sheets to order \((Q_{a0} \text{ and } Q_{a1})\) and the number of put and call options on aluminium futures to buy \((N_p \text{ and } N_c)\). 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.

2.2.2.1 Cost of initial inventories.

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

\[
Q_{a0}(S_0 - \tilde{S}_1 e^{-rT_0}) + fQ_{a0}h_{a0}T_0 e^{-rT_0}
\]

where, \(r\) represents the weekly risk-free rate of return and \(f\) is an equivalence factor that converts aluminium tonnes 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 aluminium 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 2.1.1. 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 (gain) associated with \(Q_{a1}\) is given by:

\[
Q_{a1}(\tilde{S}_1 e^{-rT_0} - S_0)
\]

2.2.2.2 Cost of put and call options.

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

\[
N_p p_0 + N_p p_0 h_{op} T_0 e^{-rT_0} - N_p e^{-rT_0} \text{Max}\{(K - \tilde{F}_1), 0\}
\]

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

\[
N_c c_0 + N_c c_0 h_{op} T_0 e^{-rT_0} - N_c e^{-rT_0} \text{Max}\{(\tilde{F}_1 - K), 0\}
\]

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.

2.2.3 Decisions and costs in second time span \((T_1)\)

Over the time period \(T_1\), can production and beer filling and packing precede the realisation 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 realisation 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 minimise holding and stockout costs while meeting lead time constraints.

2.2.3.1 Stockout costs.

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

\[
\sum_{j=6}^{13} \text{Max}\{(d_j - B_{0j}), 0\} e^{-rT_{6+j}}
\]

This cost is incurred when the beginning inventory in distribution centre \((B_{0j})\) is less than the weekly demand.

2.2.3.2 Holding costs.

Equations (6)–(8) determine the present value of the holding costs associated with the inventory of aluminium sheets, empty cans and canned beer, respectively.

\[
\sum_{j=1}^{13} E_{a0}(u_0 h_{a0} + u_1 h_{a1}) e^{-r(T_0 + j)}
\]

\[
\sum_{j=1}^{13} E_{b0}(u_0 h_{b0} + u_1 h_{b1}) e^{-r(T_0 + j)}
\]

\[
\sum_{j=1}^{13} E_{c0}(u_0 h_{c0} + u_1 h_{c1}) e^{-r(T_0 + j)}
\]
where, \( u_0 \) and \( u_1 \) are the proportions of aluminium 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 \( h_{i0} > h_0 \) and \( h_{i1} > h_1 \). 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.

2.2.4 Objective function
The objective of our model is to optimise the performance of the supply chain by minimising the expected total opportunity cost \( E(\text{TOC}) \) along the supply chain, where the TOC is the summation of Equations (1) through (8).

\[
\text{Min } E(\text{TOC})
\]

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

\[
B_{a1} = fQ_a
\]

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

\[
Q_a = Q_{a0} + Q_{a1}
\]

\[
M_{ij} = \text{Min}(B_{ij}, \bar{d}_j) \text{ for } j = \{6, \ldots, 13\}
\]

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.

\[
\text{VAR} \leq \nu
\]

Constraint (15) captures the degree of risk aversion within the supply chain. The value of the upper bound \( \nu \) on the VAR of the total opportunity cost \( \text{TOC} \) is a function of the risk management policy to be collectively determined by the supply chain members.

\[
Q_{a0}, Q_{a1} \leq q_a
\]
\[ N_p, N_c \leq n \tag{17} \]

\[ Q_{by} \leq q_b \quad \text{for } j = \{6, \ldots, 13\} \tag{18} \]

\[ Q_{cy} \leq q_c \quad \text{for } j = \{5, \ldots, 12\} \tag{19} \]

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

For lack of space, we omit in this paper the formulations of other constraints that: (i) ensure transfer of inventories remaining at the end of one week to the next week and (ii) ensure inventory flow conservation every week for the inventories of aluminium sheets, empty cans and beer.

### 2.3 Sequential model

The integrated model represents a centralised decision-making approach based on which operational and financial risk management decisions are made simultaneously. This approach is not widely used by firms. Instead, different functional areas make operational risk management decisions and financial risk management decisions independently. We represent this latter approach with a sequential model that consists of two sub-models: (i) the operational risk management sub-model and (ii) the financial risk management 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 risk management sub-model that solves for \( N_p \) and \( N_c \) to minimise the expected total opportunity cost. The optimal values of the decision variables associated with the sequential model are the values optimised by the operational sub-model and then by the financial risk management 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 risk management sub-model.

### 3. Experiments

#### 3.1 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 aluminium 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 values 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, an optimal 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, APV, is a source of uncertainty encountered at the supply chain’s upstream. This volatility is captured by the annualised standard deviation of returns on both the aluminium spot and aluminium futures, \( \sigma_1 \) and \( \sigma_2 \), that are used to estimate the spot and futures price, respectively, in Equations (A.1) and (A.2), in Appendix A, which explains the process used to simulate aluminium spot and futures prices. We considered three levels of APV, each level being represented by a value of \( \sigma_1 \) and a value of \( \sigma_2 \). The values of \( \sigma_1 \) of 25.9% and \( \sigma_2 \) of 23.9% which were estimated from historical data according to the procedure explained in Appendix A, are considered as ‘base’ values.

Table 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 15–6.7% are consistent for the three factors.
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; (iii) APV is incorporated through \(\sigma_1\) and \(\sigma_2\) that are used to simulate \(S_1\) and \(F_1\), respectively, as explained in Appendix A.

### 3.2 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, \(E(\text{TOC})\). This cost is the response variable that we use to compare the effects of treatment combinations. We use a simulation-based optimisation tool provided by @RISK, which is part of the Decision Tools Suite provided by Palisade, to determine the values of the decision variables that minimise \(E(\text{TOC})\) under the relevant constraints. Starting with initial values of the decision variables, the optimisation involves running a large number of simulations. Each simulation consists of 10,000 iterations. For each iteration, random values of the probabilistic inputs \((S_1, F_1, \text{and } d_j)\) 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 a number of simulations as replications on each of the 81 model versions and record the values of \(E(\text{TOC})\). These values then represent the response variable in the replications for each treatment combination in the experimental design.

### 3.3 Values of major parameters

The values used for the major parameters in the 81 versions of the model are summarised in Table 2. Most of these values are based on information provided by a major brewery. Values of few parameters are based on assumptions, as indicated in Table 2. Hence, the findings need to be conceived in a company-specific context.

We used the data published by the LME for the dates from 6 January to 30 March 2010 to estimate standard deviations on aluminium 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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source/Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S_0)</td>
<td>$2287</td>
<td>London Metal Exchange (LME), spot price of aluminium on 31 March 2010</td>
</tr>
<tr>
<td>(F_0)</td>
<td>$2319</td>
<td>LME, closest to maturity futures price of aluminium on 31 March 2010</td>
</tr>
<tr>
<td>(c_0 = p_0)</td>
<td>$105</td>
<td>Calculated using the Black model (Hull (2006), 332–333))</td>
</tr>
<tr>
<td>(K)</td>
<td>$2319</td>
<td>Exercise price of at-the-money options</td>
</tr>
<tr>
<td>(T_0)</td>
<td>12 weeks</td>
<td>Assumed to capture significant fluctuations in aluminium spot and futures prices</td>
</tr>
<tr>
<td>(f)</td>
<td>13.38 kg/1000 cans</td>
<td>Data provided by a major brewery</td>
</tr>
<tr>
<td>(r)</td>
<td>0.192% weekly</td>
<td>Assumed (equivalent to 10% annual rate used by Shanker and Balakrishnan (2008))</td>
</tr>
<tr>
<td>(h)</td>
<td>18%</td>
<td>Estimated</td>
</tr>
<tr>
<td>(\tilde{h})</td>
<td>36%</td>
<td>Holding cost marked up to capture special logistics requirements</td>
</tr>
<tr>
<td>(n)</td>
<td>4000 tonnes</td>
<td>Based on assumed financial constraint</td>
</tr>
<tr>
<td>(q_a)</td>
<td>4000 tonnes</td>
<td>Based on assumed operational constraint</td>
</tr>
<tr>
<td>(q_b)</td>
<td>30 million cans</td>
<td>Based on operational constraint</td>
</tr>
<tr>
<td>(q_c)</td>
<td>60 million cans</td>
<td>Based on operational constraint</td>
</tr>
</tbody>
</table>
prices are determined using Black’s model as described in Hull (2006, 332–333). Considering the exploratory nature of our study, we incorporated a 12 weeks period between $t_0$ and $t_1$ to capture any significant fluctuations in aluminium spot and futures prices. Following Shanker and Balakrishnan (2008) and Ritchken and Tapiero (1986), an annualised risk-free rate of 10% was assumed. Thus, an equivalent weekly return of 0.192% is used in Equations (1) to (8) as $T_0$ and $T_1$ are in weeks. The value of the stockout cost used in our model is obtained through private communications with a major brewery.

4. Analyses of results and managerial insights

In this section, we compare the performance of the integrated model with the performance of the sequential model. The comparison is based on the difference in the expected total opportunity cost between the two models, as well as the difference in making the integrated operational and financial risk management decisions in $T_0$. While the inventory flow decisions in $T_1$ definitely have an impact on the total opportunity cost, we do not discuss them in this paper for brevity. We discuss these decisions in two model extensions in which we incorporate variability in lead time (Bandaly, Satir, and Shanker 2013) and foreign exchange risk (Bandaly, Shanker, and Satir 2012). However, it is vital to note that the decisions made in the two time spans are related. The holding costs of surplus quantities carried in $T_1$ are functions of the unit holding costs determined by the proportions of aluminium quantities purchased at $t_0$ and $t_1$ (captured in Equations (6)–(8)). Furthermore, all the decisions have a combined impact on the VAR of the total opportunity cost (Equation (15)).

4.1 Results

Table 3 presents the main optimisation 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%). The coding of the various treatments is presented in Table 3. For the statistical analyses and managerial insights to follow, we present in Table 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 $E(\text{TOC})$ 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 $E(\text{TOC})$ and a standard deviation. In Table 3, $E(\text{TOC})$ and Dev are the means of their corresponding values in the eight replications of each treatment.

Table 3 reveals that $E(\text{TOC})$ obtained for each of the three models satisfies the following three intuitive patterns:

- For the same demand standard deviation and the same APV: When VAR increases, $E(\text{TOC})$ decreases (e.g. $E(\text{TOC})_{119} > E(\text{TOC})_{110} > E(\text{TOC})_{101}$)
- For the same VAR and the same APV: When demand standard deviation increases, $E(\text{TOC})$ increases (e.g. $E(\text{TOC})_{107} < E(\text{TOC})_{104} < E(\text{TOC})_{101}$)
- For the same VAR and the same demand standard deviation: When APV increases, $E(\text{TOC})$ increases (e.g. $E(\text{TOC})_{103} < E(\text{TOC})_{102} < E(\text{TOC})_{101}$)

4.2 Comparison of integrated and sequential models and managerial insights

In this section, we present the results from Table 3 in two way Tables 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.

4.2.1 Overall superiority of the integrated model over the sequential model

Table 3 reveals that the integrated model performs better than the sequential model in all the cases, except for cases 3, 25 and 26. 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: $(E(\text{TOC})_{\text{sequential model}} - E(\text{TOC})_{\text{integrated}}) / E(\text{TOC})_{\text{integrated}} \times 100$. This percentage difference is presented in Table 4.
Table 3. Optimisation results for the experimental design.

<table>
<thead>
<tr>
<th>Factor level</th>
<th>Sequential model</th>
<th>Operational sub-model</th>
<th>Financial hedging sub-model</th>
<th>Integrated model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$E(\text{TOC})$</td>
<td>$\text{Dev}$</td>
<td>$Q_{a0}$</td>
</tr>
<tr>
<td>1.5</td>
<td></td>
<td>S01</td>
<td>596.9</td>
<td>716.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B02</td>
<td>599.0</td>
<td>810.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H03</td>
<td>612.8</td>
<td>803.1</td>
</tr>
<tr>
<td>4.5</td>
<td></td>
<td>L04</td>
<td>784.5</td>
<td>609.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B05</td>
<td>783.6</td>
<td>652.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H06</td>
<td>790.2</td>
<td>649.2</td>
</tr>
<tr>
<td>5.2</td>
<td></td>
<td>L07</td>
<td>944.2</td>
<td>628.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B08</td>
<td>958.2</td>
<td>618.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H09</td>
<td>960.6</td>
<td>616.2</td>
</tr>
<tr>
<td>1.8</td>
<td></td>
<td>L10</td>
<td>522.6</td>
<td>983.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B11</td>
<td>545.6</td>
<td>1074.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H12</td>
<td>575.1</td>
<td>1064.3</td>
</tr>
<tr>
<td>4.5</td>
<td></td>
<td>L13</td>
<td>645.7</td>
<td>980.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B14</td>
<td>677.6</td>
<td>1006.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H15</td>
<td>723.2</td>
<td>1085.8</td>
</tr>
<tr>
<td>5.2</td>
<td></td>
<td>L16</td>
<td>873.4</td>
<td>734.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B17</td>
<td>895.9</td>
<td>738.5</td>
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<td></td>
<td></td>
<td>H18</td>
<td>908.1</td>
<td>807.3</td>
</tr>
<tr>
<td>2.1</td>
<td></td>
<td>L19</td>
<td>496.0</td>
<td>1059.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B20</td>
<td>510.7</td>
<td>1192.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H21</td>
<td>553.1</td>
<td>1168.8</td>
</tr>
<tr>
<td>4.5</td>
<td></td>
<td>L22</td>
<td>592.4</td>
<td>1141.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B23</td>
<td>607.6</td>
<td>1136.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H24</td>
<td>647.6</td>
<td>1183.2</td>
</tr>
<tr>
<td>5.2</td>
<td></td>
<td>L25</td>
<td>710.4</td>
<td>1051.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B26</td>
<td>760.1</td>
<td>1013.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H27</td>
<td>801.5</td>
<td>1024.4</td>
</tr>
</tbody>
</table>

Notes: $E(\text{TOC})$: Expected total opportunity cost (in thousands of dollars); $\text{Dev}$: Standard deviation of TOC (in thousands of dollars); $Q_{a0}$: Quantity of aluminium purchased at time $t_0$ (in million cans); $Q_{a1}$: Quantity of aluminium purchased at time $t_1$ (in million cans); $N_p$: number of put options; $N_c$: number of call options.
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. The former is a supply chain with a larger appetite for risk and the latter is a supply chain with a lower appetite for risk. Improvement in $E(\text{TOC})$ 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 risk management decisions except for those situations in which the APV 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.

4.2.2 Operational and financial risk management

In this section, we discuss the operational and financial risk management strategies incorporated in the integrated and sequential models. While financial risk management is executed through purchasing put and call options, operational risk management can be represented by the ratio ($u_0$) of the quantity of aluminium sheets purchased at $t_0$ to the total quantity purchased at $t_0$ and $t_1$.

Operational Risk Management: A supply chain using the sequential model buys at time $t_0$ a proportion of its total aluminium quantity that is larger than that purchased by a supply chain using the integrated model. Table 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.

As both inventory and financial risk management decisions are made simultaneously in the integrated model, the supply chain is hedged against a possible increase in aluminium prices by the purchase of a quantity $Q_{a0}$ of aluminium 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 aluminium 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 the supply chain’s willingness to wait (and take chances) to buy a higher quantity of aluminium at $t_1$.
- For VAR values of 1.5 and 1.8, for a given SDD: As SDD increases, $u_0$ increases, pointing to a cautious behaviour in terms of buying higher quantities of aluminium earlier at $t_0$.

Financial Risk Management: Table 3 depicts the difference in the financial risk management strategies adopted in the integrated and the sequential models. In the latter model, as financial risk management decisions are made after inventory levels are determined, we observe the contribution of these decisions in further reducing the $E(\text{TOC})$

<table>
<thead>
<tr>
<th>SDD</th>
<th>VAR</th>
<th>Integrated</th>
<th>Sequential</th>
<th>Integrated</th>
<th>Sequential</th>
<th>Integrated</th>
<th>Sequential</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.8</td>
<td>1.5</td>
<td>22–23%</td>
<td>27–28%</td>
<td>7–11%</td>
<td>14–24%</td>
<td>7–10%</td>
<td>8–22%</td>
</tr>
<tr>
<td>4.5</td>
<td>1.8</td>
<td>29–33%</td>
<td>39%</td>
<td>10–11%</td>
<td>18–29%</td>
<td>4–5%</td>
<td>8–15%</td>
</tr>
<tr>
<td>5.2</td>
<td>2.1</td>
<td>32–34%</td>
<td>44–45%</td>
<td>31%</td>
<td>37–41%</td>
<td>5–23%</td>
<td>8–25%</td>
</tr>
</tbody>
</table>
optimised by the operational sub-model. (This contribution is measured by the percentage difference between the corresponding costs, as given by \((E(\text{TOC})_{\text{operational}} - E(\text{TOC})_{\text{financial risk management}})/E(\text{TOC})_{\text{operational}}) \times 100\) and is presented in Table 6.

The results depicted in Tables 5 and 6 reveal a negative relationship between the effects of financial risk management on \(E(\text{TOC})\) in the sequential model and the degree of operational risk management \((u_0)\). At \(\text{VAR} = 1.5\), \(u_0\) is the highest and financial risk management has no significant effect. At \(\text{VAR} = 1.8\) and 2.1, the effects are most significant when \(\text{SDD} = 3.8\) in which case \(u_0\) is the lowest. When \(\text{SDD} = 4.5\), financial risk management has a significant effect only when \(\text{APV}\) is low, in which case \(u_0\) is the lowest.

Managerial Insights: Whether integrated or individual risk management models are used, a less risk averse supply chain hedges aluminium price risk with much less physical quantity of aluminium 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 risk management 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. However, in certain business environments, the potential improvement in the supply chain performance may not justify the effort required to implement the financial hedging decision.

4.3 Statistical analyses

As the main objective of our research is to study the benefits of integrating operational and financial risk management 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 risk management 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 optimisation runs. The software generates a quadratic regression model that explains the variations in the response variable, \(E(\text{TOC})\), for each of the integrated model and the sequential model. The quadratic regression model includes terms representing the three factors (\(\text{VAR}, \text{SDD}\) and \(\text{APV}\)) 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 risk management models used for optimisation. Thus, in the following discussion, the regression integrated model is the model we use to predict \(E(\text{TOC})\) that can be optimised 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 \(E(\text{TOC})\) within and between the integrated and sequential models.

4.3.1 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 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

<table>
<thead>
<tr>
<th>SDD</th>
<th>(\text{VAR} = 1.5)</th>
<th>(\text{VAR} = 1.8)</th>
<th>(\text{VAR} = 2.1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.8</td>
<td>1.1–2.1%</td>
<td>3.8–6.4%*</td>
<td>5.5–6.7%*</td>
</tr>
<tr>
<td>4.5</td>
<td>0.3–0.6%</td>
<td>0.6–3.1%*</td>
<td>2–5.1%*</td>
</tr>
<tr>
<td>5.2</td>
<td>0%</td>
<td>0.2–1.2%</td>
<td>0.7–2.3%</td>
</tr>
</tbody>
</table>

*Statistically significant at 0.05 significance level.
significant effects on $E$(TOC). We discuss these interactions and provide managerial insights in the following subsection.

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 vs. 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.

Table 7. ANOVA results for aggregate regression model.

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of squares</th>
<th>df</th>
<th>Mean square</th>
<th>$F$ value</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>6.51E + 12</td>
<td>52</td>
<td>1.25E + 11</td>
<td>7686</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>A-VAR</td>
<td>1.66E + 11</td>
<td>1</td>
<td>1.66E + 11</td>
<td>10,165</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>B-SDD</td>
<td>6.84E + 11</td>
<td>1</td>
<td>6.84E + 11</td>
<td>41,983</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>C-APV</td>
<td>1.79E + 10</td>
<td>1</td>
<td>1.79E + 10</td>
<td>1098</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>D-Model</td>
<td>2.12E + 10</td>
<td>1</td>
<td>2.12E + 10</td>
<td>1304</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>AB</td>
<td>2.24E + 10</td>
<td>1</td>
<td>2.24E + 10</td>
<td>1374</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>AC</td>
<td>3.18E + 09</td>
<td>1</td>
<td>3.18E + 09</td>
<td>195</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>AD</td>
<td>6.16E + 08</td>
<td>1</td>
<td>6.16E + 08</td>
<td>38</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>BC</td>
<td>2.16E + 09</td>
<td>1</td>
<td>2.16E + 09</td>
<td>133</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>BD</td>
<td>9.51E + 08</td>
<td>1</td>
<td>9.51E + 08</td>
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Figure 2. Effects of VAR on $E$(TOC) at lowest and highest levels of SDD and APV.
4.3.2 Main and interaction effects

As illustrated in Table 7, all the factors, as well as their interactions, have significant effects on \( E(\text{TOC}) \). Figures 2–4 illustrate the main effects of the factors and their interaction effects. Each figure depicts the change in \( E(\text{TOC}) \) 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 \( V\text{AR} \), \( S\text{DD} \) and \( A\text{PV} \) on \( E(\text{TOC}) \) are visually evident in Figures 2–4. As noted in Section 4.1, there is a negative relationship between \( V\text{AR} \) and \( E(\text{TOC}) \), and a positive relationship between \( S\text{DD} \) and \( A\text{PV} \) with \( E(\text{TOC}) \). However, the degree of impact of the three factors on \( E(\text{TOC}) \) vary between the integrated and sequential models. In Figure 3(c), for example, the marginal decline in \( E(\text{TOC}) \) as \( V\text{AR} \) increases is much lower in the sequential model than in the integrated model. On the other hand, while \( E(\text{TOC}) \) exhibits a continuous decline as \( V\text{AR} \) increases in the sequential model, the change is minimal in the integrated model once \( V\text{AR} \) reaches the level of 1.9.

While in most of the cases the integrated model results in a lower \( E(\text{TOC}) \) compared to that of the sequential model, some exceptions can be observed nevertheless. Figure 2(b) and (c) reveal cases where \( E(\text{TOC}) \) of the integrated model is higher than that of the sequential model. This occurs when \( V\text{AR} \) is above 2 in the former figure and below 1.54 in the latter. Similar observations can be made in Figure 3(b) when \( S\text{DD} \) is higher than 4.9 and in Figure 3(c) when \( S\text{DD} \) is below 3.94. Figure 4(a) and (d) also reveal that the sequential model outperforms the integrated model when \( A\text{PV} \) is higher than 26.4% and lower than 24.7%, respectively.

Managerial Insights: (i) In general, a less risk averse (LRA) supply chain (willing to accept high \( V\text{AR} \) 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 \( A\text{PV} \). (iii) The supply chain would not always be able to exploit the benefits of integrating operational and financial risk management decisions.
Under certain business environments, such as described above, the integrated model may not outperform the sequential model.

While results in Table 3 show positive and negative relationships between each factor and $E(\text{TOC})$, Figures 2–4 provide visual insights about these relationships. Figure 2 exhibits clear changes in the response of $E(\text{TOC})$ to variations in VAR under the different combinations of SDD and APV. This is true for both the integrated and sequential models. For example, the $E(\text{TOC})$ curve changes from a concave to a convex curvature when SDD changes from 3.8 in Figure 2(a) to 5.2 in Figure 2(b). In the integrated model, when SDD is low, $E(\text{TOC})$ does not improve in the cases when VAR becomes higher than 1.9 million dollars. On the other hand, when SDD is high, $E(\text{TOC})$ continues declining as VAR increases and it reaches a minimum value at VAR = 2.1 million dollars. Similarly, Figure 4 exhibits clear changes in the response of $E(\text{TOC})$ to variations in APV under the different combinations of SDD and VAR. For example, the graph of $E(\text{TOC})$ in the integrated model changes from curvilinear in Figure 4(c) to linear with a mild slope in Figure 4(d).

Managerial Insights: (i) In contrast with the general relationship observed between VAR and $E(\text{TOC})$, 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 $E(\text{TOC})$ in Figure 2(a) and (c). (ii) Under low-demand variability and using the integrated model, a MRA supply chain benefits from decline in APV much more than a LRA supply chain. On the other hand, when demand variability is high, a LRA supply chain benefits from decline in APV much more than MRA supply chain.

The quadratic regression model allows the prediction of $E(\text{TOC})$ for any factor level within the range defined. As examples, Figures 5 and 6 depict a three-dimensional 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 visualise 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 5 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 6, 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 6 (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.

5. Concluding remarks
The SCRM integrated model developed captures the supply chain risk management process that requires the collaboration of supply chain members (aluminium 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 risk management decisions to minimise 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 in which risk management decisions are made independently by functional units, but also more robust when subjected to changing business environments. The findings also shed light on the business environment in which the integrated model 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 APV. 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 APV is high. The type of risk management strategy used depends also on the risk aversion level and the demand variability. In general, the supply chain studied has managed risk more with operational methods and less with financial instruments when faced with higher demand variability. However, as the supply chain becomes less risk averse, it tends to manage risk less with operational and more with financial instruments.

The model presented here had been extended by considering stochastic lead time for empty can production and incorporating fluctuations in foreign currency exchange rates when purchasing aluminium from a foreign supplier. The former case was reported in Bandaly, Satir, and Shanker 2013, and the latter in Bandaly, Shanker, and Satir 2012. The SCRM integrated model developed can be further extended in a number of different operational and financial risk management directions. As possible extensions, multiple commodities (e.g. aluminium and barley) and multiple suppliers (of aluminium cans and barley) can be incorporated into the model. The integrated decisions can be modelled as a dynamic process. The use of futures and/or forward contracts instead of options might be more effective under this scenario.

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References
Appendix A. Simulating the probabilistic input

A.1 Aluminium spot and futures prices

Assuming that aluminium spot and futures prices are lognormally 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,

\[
S_1 = S_0 \times \exp \left[ \left( \mu_1 - \frac{\sigma_1^2}{2} \right) T + \sigma_1 \sqrt{T} \varepsilon_1 \right] \tag{A.1}
\]

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

where \( S_0 \) and \( F_0 \) are spot and futures prices, respectively, at the current time \( t_0 \), \( \mu_1 \) and \( \mu_2 \) are the annualised mean of the continuously compounded returns on the spot and on the futures, respectively, and \( \sigma_1 \) and \( \sigma_2 \) are the annualised standard deviations of the continuously compounded returns on the spot and on the futures, respectively; \( \mu_1, \mu_2, \sigma_1 \) and \( \sigma_2 \) 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. \( \varepsilon_1 \) and \( \varepsilon_2 \) represent standard normal random variables whose correlation is \( \rho_{12} \) 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.

\( \varepsilon_1 \) and \( \varepsilon_2 \) are simulated as follows:

\[
\varepsilon_1 = x_1, x_1 \sim \Phi(0, 1) \tag{A.3}
\]

\[
\varepsilon_2 = \rho_{12} x_1 + x_2 \sqrt{1 - \rho_{12}^2}, x_2 \sim \Phi(0, 1) \tag{A.4}
\]

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.