ESSAYS ON RISK MANAGEMENT IN SUPPLY CHAINS

By

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ABSTRACT

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Supply Chain Risk management (SCRM) is receiving increased attention recently due to the impact of unexpected disruptions (e.g., 2011 Tsunami in Japan, 2011 flooding in Thailand, etc.) and delays. However, managing risk in supply chains is a difficult task because of the inherent complexity of the global supply chain networks. My dissertation focuses on three essays related to risk management in supply chains with emphasis on strategic, tactical, and operational levels of decision-making.

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INTRODUCTION

Supply chain risk management (SCRM) is receiving increased attention recently due to the impact of unexpected disruptions (e.g., 2011 Tsunami in Japan, 2011 flooding in Thailand, etc.) and delays. Within the broad rubric of SCRM, my research specifically focuses on i) supplier and risk mitigation strategy selections, ii) sourcing decisions and information sharing under risk, and iii) transportation risk management. The Three essays in my dissertation address each of these aforementioned topics with emphasis on strategic, tactical, and operational decision making. The following paragraphs discuss each of these essays.

The first essay focuses on supplier selection and risk mitigation strategies. Specifically, with the growing emphasis on supply risk, consideration of risk aspects in supplier selection decisions and risk mitigation are important issues faced by companies. While extant literature has proposed a variety of tools and techniques for effective supplier selection, few approaches are proposed in incorporating risk factors in supplier selection and mitigation decisions. I address the issue of simultaneously considering supplier selection and risk mitigation during a given planning horizon in a supply chain. I also argue that *risk mitigation should be considered at the supplier selection phase with a mixture of upstream and downstream risk mitigation strategies rather than separately applying a sole strategy*. In this essay, the results demonstrate that the simultaneous consideration of upstream and downstream risk mitigation strategies (at the supplier selection phase) has the potential for better performance than separately using individual strategies. However, the mixed strategies do not always guarantee that they outperform individual strategies, which means that the alignment between the strategies is critical for improved performance.

The second essay of my dissertation focuses on sourcing decisions under conditions of risk and information sharing among supply chain partners. Specifically, this essay considers a manufacturer's sourcing decisions in a supply chain with three players (manufacturer, first-tier supplier, and second-tier supplier). In this scenario, the manufacturer sources identical and critical components from a single first-tier supplier (FT). The FT in turn sources raw materials from a single second-tier supplier (ST). The suppliers in both tiers are unreliable, i.e., prone to disruption risk, and there are no viable alternative sources. In such a setting, increase in supply chain visibility through information sharing could be an effective disruption management strategy for the manufacturer. However, the FT may not be willing to share the ST's disruption risk with the manufacturer due to competitive issues. Given such circumstances, I demonstrate the conditions under which information sharing between the manufacturer and the FT results in improved profits for both parties, i.e., information sharing of upstream (ST) disruption risk by FT and downstream demand risk by the manufacturer. In addition, the sourcing decisions of the manufacturer under the absence and presence of information sharing are investigated. Finally, I identify effective ways to induce the FT in sharing information regarding the ST's disruption risk, i.e., the efficacy of information swap between FT and the manufacturer based on the value of information and in deriving optimal pricing strategies.

The third essay in my dissertation focuses on risks faced in transportation decisions. In recent years, access to freight transportation capacity has become a constant issue in the minds of logistics managers due to record capacity shortages. In a buyer-seller relationship, reliable, timely, and cost-effective access to transportation is critical to the success of such partnerships. Given these circumstances, shippers are in search for guaranteed capacity contracts with 3PLs to increase their access to capacity and respond effectively to customer requirements. With this new opportunity, 3PL providers must focus on approaches that can assist them in analyzing their options as they promise guaranteed capacity to shippers when faced with uncertain demand and related risks in transportation. In this essay, I analytically analyze three capacity-based risk mitigation strategies and their combinations using industry based data in providing insights on which strategy is preferable to the 3PL provider and under what conditions. I posit that the selection of a strategy is contingent on several conditions faced by both the shipper and the carrier. My approach has a high degree of practical utility in that a 3PL provider can utilize our decision models to effectively analyze and visualize the trade-offs between the different strategies by considering appropriate cost and demand data.

ESSAY 1

MODELS FOR SUPPLIER SELECTION AND RISK MITIGATION:

A HOLISTIC APPROACH

Abstract

With growing emphasis on supply risk, consideration of risk aspects in supplier selection is an important issue faced by firms. While extant literature has proposed a variety of tools and techniques for effective supplier selection, few approaches, if any, are proposed in incorporating risk mitigation strategies in supplier selection decisions. To this end, this paper fills this gap, by considering a variety of risk factors in supplier selection, which are both quantitative and qualitative in nature, and tests the efficacy of alternative risk mitigation strategies in this context. Moreover, we argue that both upstream and downstream risk mitigation strategies should be used simultaneous rather than focusing on a sole strategy, i.e., alignment between upstream and downstream risk mitigation is critical. We utilize multi-objective optimization based simulation in building a decision model in the context of this problem setting. We consider data from an automotive parts manufacturer in demonstrating the application of our approach.

1. Introduction

Supplier selection is one of the most important issues in supply chain management (SCM) for maintaining a competitive advantage. Traditionally, the cost aspect was solely emphasized, but recent emphasis has also been on other important factors such as quality, delivery, and flexibility in supplier selection (Sarkis and Talluri, 2002; Amid et al., 2011; Lin, 2012). As a supply chain becomes more complex, extended, and globalized, firms become more and more dependent on their suppliers. This also entails a number of unexpected negative events, which makes supplier selection more critical and difficult task compared to the past. Thus, in supplier section, it is necessary to consider factors above and beyond cost from a risk management perspective.

Recently, supply chain risk management (SCRM) has been receiving increasing attention in both academic and practitioner circles. Literature in this area has primarily focused on: i) identifying and categorizing risk drivers[1] (Chopra and Sodhi, 2004; Kull and Talluri, 2008); ii) developing risk assessment techniques (Zsidisin et al., 2004; Wang et al., 2012; Aqlan and Lam, 2015); iii) defining risk mitigation strategies (Chopra and Sodhi, 2004; Faisal et al., 2006); and iv) evaluating risk management strategies (Talluri et al, 2014; Yoon et al., 2015). It is not uncommon for companies in the same industry to face different types of risks, which leads them to emphasize and recognize that adapting tailored risk mitigation strategies is a key aspect for their success in a turbulent environment (Hauser, 2003; Chopra and Sodhi, 2004). Various risk mitigation strategies (including upstream and downstream risk mitigation strategies) have already been developed by several researchers to address specific needs of companies. Among such risk mitigation

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[1] risk drivers: factors such as events and conditions, which might increase the level of risk in supply chain (Chopra and Sodhi, 2004; Jüttner et al., 2003)

strategies, companies are more interested in efficient strategies that reduce risk without eroding profits (Talluri et al., 2013).

In this article, we address the issue of supplier selection and risk mitigation strategy selection in a simultaneous manner during a given planning horizon in a supply chain. We also argue that *risk mitigation should be considered at the supplier selection phase with a mixture of upstream and downstream risk mitigation strategies rather than separately focusing on applying a sole strategy*. Some literature studied the risk mitigation strategies and their effectiveness (e.g., Chopra and Sodhi, 2004; Schmitt, 2011; Chopra and Sodhi, 2013). Not surprisingly, several of these strategies are closely related to the supplier selection issue for mitigating upstream risk such as *having redundant suppliers*. However, there is no previous work that addresses the potential synergy between mitigation strategies related to downstream risk and supplier selection based mitigation strategies focusing on upstream risk. We conjecture that an alignment between upstream and downstream risk mitigation at the supplier selection stage can result in more effective mitigation of risk.

To this end, the contribution of this paper is two-fold. First, we propose models that integrate two important SCM issues: i) supplier selection and ii) risk mitigation strategy selection. The models demonstrate the reasons for the two aspects to be considered simultaneously rather than separately. Second, from a methodological perspective, we develop decision models, that utilize a combination of multi objective optimization and simulation approaches, for simultaneous consideration of a broad range of risk drivers, objectives, company's risk attitude, and order allocation factors. The multi objective optimization allows the simultaneous consideration of cost and risk (Yildiz et al., 2015)[2] and simulation enables us to achieve efficiency and effectiveness in deriving solutions under a given parameter set over a multi-period planning horizon (Jung et al., 2008). Thus, we expect that this combination of methodologies to provide a holistic solution to this problem environment.

The remainder of the paper is organized as follows. The next section reviews the related literature in the areas of supplier selection and risk mitigation. We then describe the problem and introduce representative risk mitigation strategies that are selected from the extant literature. The following section presents the mathematical models for supplier selection with the consideration of risk mitigation strategy selection and related analysis. Finally, we discuss the limitations of our approach and present future research directions.

2. Literature Review

Supplier selection is a very important issue in SCM, since poor judgment in supplier selection can lead to various supply base problems such as late deliveries and/or high defects rates (Smeltzer and Siferd, 1998). Gonzalesz and Quesada (2004) also found that supplier selection was the most influential factor for achieving long-term competitive advantage. Moreover, as supply chains become global, a firm's supply chain risks begin to be influenced more by outside factors in addition to internal forces. Thus, supplier selection and its associated factors are viewed from a SCRM perspective.

[2] The analytical hierarchy process (AHP) approach supports managers in prioritizing the supply chain objectives, identifying risk indicators, assessing the likelihood & potential impact of negative events, and deriving risk coverage scores logically and rationally (Gaudenzi and Borghesi, 2006; Wu et al., 2006; Kull and Talluri, 2008). The risk coverage score of an entity is defined as the degree of how well the entity can handle risks. Thus, the higher the risk coverage score (AHP score), the more reliable the entity is. Our research utilizes the AHP score in estimating risk.

Some scholars simplify the risks into two groups in supplier selection, recurrent risks and disruption risks. Tomlin (2006) considers two suppliers for a single product: one unreliable and the other reliable but more expensive. He demonstrates that supplier diversification strategy is favored over an inventory reserve approach if unfavorable events are rare but long (disruption risk), whereas an inventory mitigation approach is preferred if unfavorable events are frequent but short (recurrent risk). He finds that the features of suppliers such as reliability and flexibility and the nature of risk (disruption or recurrent) are keys for success in supplier selection. Chopra et al. (2007) also present similar findings and also emphasize the importance of decoupling recurrent risks and disruption risks, and the importance of supplier's features such as reliability when managers are selecting suppliers. However, there also have been more detailed traditional dimensions in supplier selection: cost, quality, delivery, service and innovation (Lee et al., 2001; Krause, 2001). Gaonkar and Viswanadham (2004) develop a conceptual and analytical framework for forming supply base that minimizes potential losses caused by supply chain risk. They incorporate the traditional dimensions into categorizing recurrent risk and disruption risk. Kull and Talluri (2008) propose a more feasible and meaningful decision tool for supplier selection in risk management context by relaxing the categorization process. Based on the traditional dimensions, they develop a framework for risk assessment and effectively integrate the risk issues into supplier evaluation using AHP.

The relationship between investment and its expected returns is a fundamental issue in businesses. We know that a set of actions, which provide higher returns and/or improved risk coverage abilities require a certain amount of upfront investment costs. In the same vein, Hendricks and Singhal (2005) state that investments in increasing reliability and responsiveness of supply chains could be viewed as buying insurance against the economic loss from disruption. However, investment in changes or development is itself inherently risky (Hallikas et al., 2004). Therefore, careful consideration for investment decisions is a necessary part of SCRM. Kleindorfer and Saad (2005) chart a conceptual framework that trades off risk mitigation investments, including the cost of management systems, against potential losses caused by supply chain risks arising from disruptions. This investment evaluation approach for risk management may supplement the supplier selection approach. However, the extant investment evaluation approaches only focus on disruptions. Risk assessment process is generally composed of two dimensions, assessing the likelihood and impact of a potential problem, i.e., likelihood$\otimes$impact. Based on this assessment process, even though recurrent risks have low impact, they have high likelihood, which makes recurrent risks equally important as disruptions. Thus, we also need to take recurrent risks into consideration while making investment decisions.

The extensive supply chain risk sources and the broad range of risk management approaches result in various risk mitigating strategies in supply chains. Some recent studies have sought to define risk-mitigating strategies by considering the strategic "fit" concept (Jüttner et al., 2003; Chopra and Sodhi, 2004). Jüttner et al. (2003) note four types of risk mitigation strategies that can be adapted to supply chain contexts from five generic strategies introduced by Miller (1992): (i) avoidance; (ii) control; (iii) cooperation; and (iv) flexibility. They roughly explain the suitability of each strategy with emphasis on the concept of "fit". The strategies are composed of different set of enablers that interact with each other (Faisal et al., 2006). Each enabler covers its own set of risk drivers and the interaction of enablers leads the coverage of each risk driver to interact with each other, which can be restated that the risk mitigation strategies are eventually composed of the coverage of not only individual risk drivers but also their interactions. In that sense, Chopra and Sodhi (2004) have categorized risk drivers and make a list of possible risk mitigation strategies based on the interaction of individual risks: (i) add capacity; (ii) add inventory; (iii) have redundant suppliers; (iv) increase responsiveness; (v) increase flexibility; (vi) aggregate or pool demand; (vii) increase capacity; and (viii) have more customer accounts.

The supplier selection literature in risk management generally does not address how the supply base formation might differ if buyers focus tactical or strategic level planning (i.e., medium to long term planning). Some recent research studies have examined long-term factors such as product life cycle issues in the supply chain risk context (Kull and Talluri, 2008), but have not specifically investigated the effect of inventory level and its dynamic nature of the relationship between periods during the planning horizon that are critical in practice. Moreover, only a few previous articles have examined the impact of a company's risk attitude on SCRM practices. We conjecture that differences in risk attitude may affect the selection of risk mitigation strategies. Furthermore, there is no systematic tool for selecting the best-fit risk mitigation strategy under the consideration of supplier selection. In this study, we propose a highly flexible and extendible decision-making methodology that takes these issues into account under the dyad of a focal company and its supply base.

3. Problem Description

We consider a three-tier supply chain composed of a focal company, potential suppliers and customers. We assume that there are multiple customers but one of these customers is more important than the rest and designated as the "main customers" (see Figure E1-1).

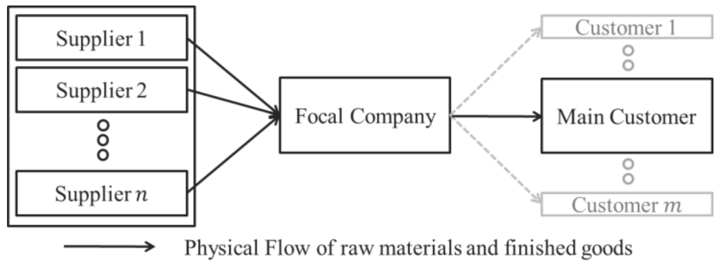

Figure E1-1: Three-tier supply chain setting

There are two conflicting goals that the focal company is trying to achieve simultaneously: One is cost minimization. The other is having a reliable flow of supplies from the supply base (upstream risk mitigation) and dealing with customer's demand uncertainty (downstream risk mitigation), i.e., risk minimization or reliability maximization. We assume that each of the various potential suppliers have different levels of reliability. Thus, sourcing more from a reliable supplier decreases upstream risk and increases sourcing reliability. Similarly, in order to reduce downstream risk, the focal company might store and/or deliver redundant units of finished goods to the customer to reduce (or avoid) the shortage from defects among the delivered goods. Within this context, we consider four risk mitigation strategies, which have been also studied in the existing literature: two strategies related to supplier selection, thus mitigating upstream risk, and two strategies related internal capabilities, mitigating downstream risk. Table E1-1 summarizes the strategies from the focal company's perspective.

The first two strategies (ARS and HFS) inherently contain the supplier selection issue. However, the other two strategies (IC and IV) can be applied without modifying the existing supply base. In the following section, we first test if the strategies in Table E1-1 can reduce risk (increase reliability) and, at the same time, reduce cost (compared to base case, i.e., without applying any mitigation strategies). In addition, we will investigate if the downstream risk mitigation strategies (IC and IV) should be considered at the supplier selection stage with upstream risk mitigation strategies (ARS and HFS) for better results.

Table E1-1: Risk mitigation strategies (Chopra and Sodhi, 2004; Tomlin, 2006; Talluri et al., 2013)

Mitigation Strategy	**Approach/ Classification**	**Description**
Acquire redundant supplier(s) (**ARS**)	Upstream risk mitigation/ Redundancy	Increase the number of supplier, i.e., modify existing supply base from single to dual/multiple sourcing
Have more flexible supplier(s) (**HFS**)	Upstream risk mitigation/ Flexibility	Replace existing supplier(s) with new supplier(s) that offers more flexibility in volume
Increase capacity (**IC**)	Downstream risk mitigation/ Redundancy	Increase internal production/manufacturing capacity by 20% of existing capacity
Increase inventory capacity (**IV**)	Downstream risk mitigation/ Redundancy	Increase inventory carrying capacity by 20% of existing capacity

4. Model

Supplier selection and risk mitigation strategy selection is a medium term tactical level planning problem (Cheaitou and Khan, 2015). Thus, we consider a one year planning model with weekly demand and supply replenishment. We develop a multi-period stochastic optimization problem with fifty two periods, by utilizing multi-objective mixed integer programming (MOMIP), which is a suitable approach for considering two conflicting objectives.

We assume that the focal company produces one type of product. Without loss of generality, we further assume that the focal company requires one unit of raw material to produce one unit of finished product (Zimmer, 2002).

4.1. Base Model

The problem is inherently a stochastic multi-stage decision problem in the operating variables and involving several sets of operating and structural constraints. Each decision stage corresponds to a planning period (denoted by t).

- **Objective Functions:**

$$\begin{aligned} \text{Min} \sum_i c_i x_{i1} + \mathrm{E}_{\theta_1}\Bigg[& \text{Min } \left(hI_1 + l(\mathrm{Y}_1 + O_1) + pS_1\right) + \sum_i c_i x_{i2} \\ & + \mathrm{E}_{\theta_2}\Bigg[\text{Min } \left(hI_2 + l(\mathrm{Y}_2 + O_2) + pS_2\right) + \sum_i c_i x_{i3} \\ & + \mathrm{E}_{\theta_3}\left[\cdots + \mathrm{E}_{\theta_T}[\text{Min } (hI_T + l(\mathrm{Y}_T + O_T) + pS_T)]\right]\Bigg]\Bigg] + f_i z_i \end{aligned} \qquad \text{(1) cost}$$

$$\begin{aligned} \text{Max} \sum_i r_i x_{i1} + \mathrm{E}_{\theta_1}\Bigg[& \text{Max } r_f(I_1 + \mathrm{Y}_1) + \sum_i r_i x_{i2} \\ & + \mathrm{E}_{\theta_2}\Bigg[\text{Max } r_f(I_2 + \mathrm{Y}_2) + \sum_i r_i x_{i3} \\ & + \mathrm{E}_{\theta_3}\left[\cdots + \mathrm{E}_{\theta_T}\left[\text{Max } r_f \mathrm{Y}_T\right]\right]\Bigg]\Bigg] \end{aligned} \qquad \text{(1) reliability}$$

Subject to

$x_{it} \le CA_i z_i$	for $\forall i$ and t	(2)
$x_{it} \ge MI_i z_i$	for $\forall i$ and t	(3)
$(1-\alpha_i)x_{it-1} \le x_{it} \le (1+\alpha_i)x_{it-1}$	for $\forall i$ and t	(4)
$I_t = I_{t-1} - \mathrm{Y}_t + \sum_i x_{it}$	for $\forall t$, $I_0 = 0$	(5)
$IL \le I_t \le IU$	for $\forall t < T$, I_T can be less than IL	(6)
$I_{t-1} + \sum_i x_{it} - \mathrm{Y}_t \le IU$	for $\forall t$	(7)
$\mathrm{Y}_t \le CA_f$	for $\forall t$	(8)
$S_t \ge D_t - \mathrm{Y}_t$	for $\forall t$	(9)

$O_t \geq Y_t - D_t$	for $\forall t$	(10)
$\sum_i z_i = N$		(11)
$x_{it}, Y_t, I_t, S_t, O_t \geq 0$ and integer and z_i is binary	for $\forall i$ and t	(12)

, where

- **Decision variables:**

x_{it} : order quantity from supplier i in period t.

Y_t : supply quantity to customer in period t.

z_i : binary variable that is 1 if supplier i is selected, 0 otherwise.

I_t : focal company's ending inventory level in period t.

S_t : amount of shortage in period t.

O_t : over-delivered amount in period t.

- **Parameters:**

c_t : unit purchasing price for supplier i.

f_i : fixed cost for supplier i

h : unit inventory holding cost.

p : unit penalty cost for shortage. $(= \overline{c_i} \cdot 1.5 \cdot 1.5)$

l : unit transportation cost. $(= \overline{c_i} \cdot 1.5 \cdot 0.18)$

CA_i : capacity of supplier i.

CA_f : capacity of focal company.

MI_i : minimum order quantity of supplier i.

α_i : volume flexibility of supplier i, $0 \leq \alpha_i \leq 1$.

D_t : random demand of period t with distribution parameter θ_t.

IL : inventory lower bound (safety stock level of the focal company).

IU : inventory upper bound (inventory holding capacity of the focal company).

N : number of supplier(s) utilized.

r_i : AHP score (reliability) of supplier i.

r_f : relative reliability of focal company. $(= \overline{r_i})$

The first term in cost objective function, Eq. (1) cost, is sourcing cost in the first planning period. The second term represents the total cost of the T-stage decisions (involving the wait and see inventory, delivered/over delivered, and shortage variables) at each planning period and the here-and-now sourcing variables of the adjacent planning period. It also includes a fixed cost for selected supplier i at the end of the cost objective function. Similarly, in the reliability objective function, Eq. (1) reliability, the first term represent reliability from the sourcing in the first period. The second term represents the total reliability of the T-stage decisions (involving the wait and see inventory and supply amount (to customer) variables) at each planning period and the here-and-now sourcing variables of the adjacent planning period. For the last period, i.e., period T, inventory is of no use, thus it is not included in the calculation of total reliability of the focal company.

The nested expectations of $\mathrm{E}_{\theta_1}\left[\mathrm{E}_{\theta_2}\left[\cdots \mathrm{E}_{\theta_T}[\,]\,\right]\right]$ denotes that the expectation is computed over the probability distribution of the cumulative demand, D_t, with parameter set θ_t up to each planning period t where the inner expectation is conditioned on the realization of the uncertain demand of the outer expectation. Thus, the sourcing variables, x_{it}, are determined after the demand requirements up to period $t-1$ have been realized but before the demand outcomes for period t and subsequent periods are known. Consequently, the decision on the sourcing variables for period t should take into account the state at the beginning of planning period t and the possible demand outcomes in later periods. This is formalized through constraint (5) which links the decisions of two adjacent planning periods. The supply variables, Y_t, take into account the demand outcomes for planning period t and serve to constrain the state variable I_t, O_t, and S_t.

The constraints, Eq. (2) - (11), are generated for each demand sample path (scenario) at each planning period in the deterministic equivalent formulation. Eq. (2) limits sourcing amount up to each supplier's capacity. Eq. (3) constrains the minimum sourcing amount for suppliers. Eq. (4) sets upper and lower bounds of sourcing amount based on the volume flexibility offered by suppliers. Eq. (5) is a typical inventory balance equation between adjacent periods. Note that I_t is determined based on demand realization up to planning period t. Eq. (6) limits upper bound of inventory level due to inventory carrying capacity of the focal company and its lower bound of inventory level due to the safety stock set by the focal company. Eq. (7) constrains the focal company's production capacity. This constraint is redundant, since Eq. (5) and (6) can take care of this. Eq. (8) limits focal company’s supply amount to the customer. Eq. (9) and (10) represent shortage and over delivered constraints, respectively. Eq. (11) restricts the number of selected suppliers.

If the demand distribution were a discrete function, the evolution of random demands over time can be represented by the tree structure. However, the total number of scenarios will be extremely large. For example, if there are Σ possible next-period demand realizations at each node, the total number of scenarios over T periods is Σ^T. Thus, for computational efficiency, we employ an approximation strategy through simulation (Jung et al., 2004) rather than applying discrete time Markov decision processes using a dynamic programming strategy.

4.2. Base MOMIP with Deterministic Model

The deterministic models are required for their execution within the simulation. The models are derived from the original stochastic program formulation developed in the previous section. In addition, the deterministic models are transformed to the MOMIP so that it can address cost and reliability simultaneously.

- **Deterministic Objective Functions:**

$$\text{Min} \sum_i \sum_t c_i x_{it} + \sum_t [hI_t + l(\mathrm{Y}_t + O_t) + pS_t] + f_i z_i \qquad (13)\ \text{cost}$$

$$\text{Max} \sum_i \sum_t r_i x_{it} + \sum_t \left[r_f (I_t + \mathrm{Y}_t)\right] - r_f I_T \qquad (13)\ \text{reliability}$$

Subject to

Eq. (2)… Eq. (8), Eq. (11), and Eq. (12)

$$S_t \geq E[D_t] - \mathrm{Y}_t \qquad \text{for } \forall t \qquad (14)$$

$$O_t \geq \mathrm{Y}_t - E[D_t] \qquad \text{for } \forall t \qquad (15)$$

The first term of Eq. (13) cost (Eq. (13) reliability) represents total procurement cost (total reliability from sourcing) over planning horizon. The second term of Eq. (13) - cost (Eq. (13) - rel.) represents total inventory carrying, delivery, and penalty costs (total reliability from inventory and supply to the customer) over planning horizon. The last tern of Eq. (13) cost (Eq. (13) reliability) implies fixed cost for supplier selection (deduction of reliability of last period's inventory). Most of all the constraints (used in the model in section 4.1) are maintained, but Eq. (9) and (10) are modified by applying expected demand, $E[D_t]$, instead of stochastic demand, D_t, for the purpose of simulation. The details of simulation will be discussed in section 5.

As noted earlier, the problem we are considering is a multi-objective optimization problem with two conflicting objective functions. We try to balance the two objectives using a min-max strategy to obtain near Pareto optimal solutions. The min-max strategy compares relative deviations from the separately attainable optimum solutions by solving the optimization problems for each objective separately, i.e., solve the optimization problem with all constraints for Eq. (13) cost and Eq. (13) reliability separately in order to derive the best possible cost (lowest cost) and best possible reliability (highest reliability). Once we have the best possible values, the two models are combined as one MOMIP with three additional variables and two additional constraints. We use the following master formulation to perform this:

- **Deterministic MOMIP for base model:**

$$\text{Min } Q \tag{16}$$

Subject to

Eq. (2)… Eq. (8), Eq. (11), Eq. (12), Eq. (14), and Eq. (15)

$$-\frac{\omega_R(RK - BR)}{BR} \leq Q \tag{17}$$

$$\frac{\omega_C(CS - BC)}{BC} \leq Q \tag{18}$$

, where Q is a variable to balance the two objectives, $Q \geq 0$ and CS and RK are corresponding value of the cost objective function (Eq. (13) reliability) and reliability function (Eq. (13) cost.), respectively.

- **Additional parameters:**

ω_C : weight for cost.

ω_R : weight for reliability.

BC : cost achieved when cost objective function (Eq. (13) - cost) is optimized in isolation

BR : reliability achieved when reliability objective function (Eq. (13) - rel.) is optimized in isolation

Note that the weights project the risk attitude of a focal company; the higher (lower) ω_C compared to ω_R, the more risk taking (risk averse) the company is. The changes in the weights enable us to perform the Pareto analysis.

4.3. Models for Sole Strategy Selection

We expect that the Pareto analysis might have a monotone increasing shape curve, i.e., total reliability is increasing in total cost, i.e., as $\frac{\omega_R}{\omega_C}$ increases the curves move from the lower left to the upper right (see Figure E1-2). However, each risk mitigation strategy has its own parameter set, which implies that each strategy's BC and BR will be different so that comparing Q values of the strategies at a certain weights, ω_C and ω_R, is meaningless. Thus, separately estimating cost/reliability curves of the strategies first, and then comparing them at a certain total cost or total reliability level will derive meaningful results.

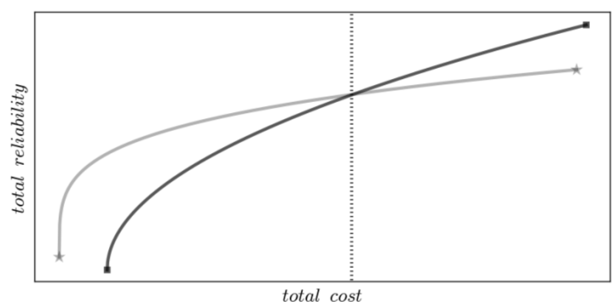

Figure E1-2: Depiction of anticipated comparison between two different strategies

As we can see the Figure E1-2, at a certain total cost level (the vertical dotted-line) the grey curve shows better performance compared to the black curve on the left side, while the black curve presents better result on the right side, since higher reliability level can be achieved at a certain cost. Each risk mitigation strategy's curve (sole strategy) can be separately drawn by the following models.

Based on the supplier(s) selected in the base MOMIP, i.e., z_i^*'s become parameters in strategy selection, we modify Eq. (1) - (18) with several additional decision variables and parameters and related constraints. Script κ denotes risk mitigation strategy, i.e., $\kappa \in \{\text{ARS, HFS, IC, IV}\}$.

- **Deterministic MOMIP for each strategy:**

$$\text{Min } Q^{\kappa} \tag{19}$$

Subject to

Eq. (2)… Eq. (8), Eq. (11), Eq. (12), Eq. (14), Eq. (15), and Eq. (17) with addition of superscript κ on all decision variables and some of focal company's parameters

Table E1-2: Modifications for sole strategy selection

Mitigation Strategy	Decision variables (As is/To be)	Parameters (As is/To be)	Modified and additional Constraints (As is/To be)
ARS	x_{it} / x_{it}^{ARS}; Y_t / Y_t^{ARS}; I_t / I_t^{ARS} S_t / S_t^{ARS} ; O_t / O_t^{ARS}	RK / RK^{ARS} CS / CS^{ARS}	$\sum_i z_i = N / \sum_i z_i^{\text{ARS}} = N^{\text{ARS}}$, where $N^{\text{ARS}} > N$ $z_i^{\text{ARS}} \geq z_i^*$
HFS	x_{it} / x_{it}^{HFS}; Y_t / Y_t^{HFS} ; I_t / I_t^{HFS} S_t / S_t^{HFS} ; O_t / O_t^{HFS}	RK / RK^{HFS} CS / CS^{HFS}	$\sum_i \alpha_i z_i^{\text{HFS}} \geq \sum_i \alpha_i z_i^*$
IC	x_{it} / x_{it}^{IC} ; Y_t / Y_t^{IC} ; I_t / I_t^{IC} S_t / S_t^{IC} ; O_t / O_t^{IC}	RK / RK^{IC} CS / CS^{IC} CA_f / CA_f^{IC}	$z_i^{\text{IC}} = z_i^*$
IV	x_{it} / x_{it}^{IV} ; Y_t / Y_t^{IV} ; I_t / I_t^{IV} S_t / S_t^{IV} ; O_t / O_t^{IV}	RK / RK^{IV} CS / CS^{IV} IU / IU^{IV}	$z_i^{\text{IV}} = z_i^*$
Modified cost objective function			
Min $\sum_i \sum_t c_i x_{it}^{\kappa} + \sum_t [h I_t^{\kappa} + l(\text{Y}_t^{\kappa} + O_t^{\kappa}) + p S_t^{\kappa}] + f_i z_i^{\kappa} + IS^{\kappa}$, where IS^{κ} is investment cost for strategy $\kappa \in \{\text{IC, IV}\}$. BC^{κ} and BR^{κ} are corresponding best possible cost and reliability when solving the problem of strategy κ in isolation of cost and reliability objective function, respectively.			

In addition, cost objective function and its corresponding BC^{κ} need to be modified and several additional constraints are required to be added. The modifications are summarized in the Table E1-2 above.

4.4. Models for Simultaneous Selection for Strategies

Based on our sample strategies, we can derive four different mixture of upstream and downstream risk mitigation strategies; ARS + IC, ARS + IV, HFS + IC, and HFS + IV. Similar to the sole strategy selection, the models are modified based on the base MOMIP. Each mixture model take upstream strategy's supplier related constraints, while taking downstream strategy's modified parameters. For example, the mixture of ARS + IC can have ARS's modified and additional constraints rather than having IC's additional constraint appeared in Table E1-2, i.e., $\sum_i z_i^{\text{ARS + IC}} = N^{\text{ARS}} = N^{\text{ARS + IC}}$ and $z_i^{\text{ARS + IC}} \geq z_i^*$. However, this mixture will apply the modified focal company's capacity, i.e., $CA_f^{\text{ARS + IC}} = CA_f^{\text{IC}}$. Moreover, the investment costs are the same as downstream risk mitigation strategies' investment costs, i.e., $IS^{\text{ARS + IC}} = IS^{\text{IC}}$.

5. Numerical Experiments and Results

The models (including reference, sole strategy selection, and simultaneous selection of strategies) are initially solved with deterministic MOMIP under expected demand. Then, the repeated simulation of the supply chain operation will be applied based on the initial solutions over the planning horizon, each with a given Monte-Carlo sample of the demands. Within each simulation, a series of planning problems are solved under the rolling horizon scheme and solutions are updated. The following summarizes the procedure for executing a timeline.

Step 0: run the deterministic base MOMIP with given state (based on the forecasted demand) to obtain the sourcing decision x_{it} for period t. (at the first iteration, $t = 1$)

Step 1: run the discrete event simulation with demand outcomes (realized demand from the Monte-Carlo sampling) for the planning period t, i.e., revise Y_t, S_t, O_t, and I_t. Note that the demand outcomes are recorded for future steps.

Step 2: update and record I_t at the end of planning period t and parameterize z_i's, i.e., fixing $z_i = z_i^*$.

Step 3: set $t = t + 1$ and go to step 0 until $t = T$.

Step 4: set $t = 1$ and initialize $z_i^\kappa = z_i^*$.

Step 5: separately run the deterministic MOMIP models (including four sole strategies and four simultaneous selection of strategies) with given state (based on the recorded forecasted demand at Step 1) to obtain the sourcing decision x_{it}^κ for period t.

Step 6: separately run the discrete event simulations for all eight models with demand outcomes (recorded at Step 1) for the planning period t, i.e., revise Y_t^κ, S_t^κ, O_t^κ, and I_t^κ.

Step 7: update and record I_t^κ at the end of planning period t and parameterize z_i^κ's, i.e., fix $z_i^\kappa = z_i^{\kappa*}$.

Step 8: set $t = t + 1$ and go to step 5 until $t = T$.

By repeating the above procedure for a sufficient number times, we measure the performance of each individual mitigation strategy as well as each mixed strategy. We run the models with the input parameters used in Kull and Talluri (2008) including information related to suppliers, focal company and customer demand. For investment cost, IS^{IC} and IS^{IV}, we employ the estimation approach used in Talluri et al. (2013). Table E1-3 indicates all the parameters used in the analysis with corresponding sources and assumptions.

By applying Monte-Carlo sampling approach, we generate one hundred sets of normally distributed synthetic demand data. We assume stationary demand D_t over planning horizon (52 weeks), i.e., $\theta_1 = \theta_2 = \cdots \theta_{52}$ with $\mu_D =$2,000,000/52 and $\sigma_D^2 = 0.2 \cdot \mu_D$.

Figure E1-3 summarizes our data sets (100 sets) from the Monte-Carlo sampling. Based on the demand data and simulation model, we initially run the base MOMIP model.

Table E1-3: Input parameters

Input Parameters	Supplier A	Supplier B	Supplier C
Monthly Capacity[a]	2,000,000/52	2,000,000/52	2,000,000/52
Minimum Order Quantity	40,000/52	40,000/52	40,000/52
Unit Price	$0.3925	$0.3850	$0. 3850
Fixed Cost	$2,000	$2,000	$2,000
Flexibility[b]	$\xi \times 0.63$	$\xi \times 0.11$	$\xi \times 0.26$
Reliability[c]	0.36	0.33	0.31

a. We assume that focal company's capacity is also 2,000,000/52
b. ξ is an arbitrary constant with range $0 \leq \xi \times 0.63 \leq 1$. Analysis is done over various $\xi = 1.0$.
c. We assume that focal company's reliability is equal to the average reliability of suppliers

	IC	IV
Investment Cost[d]	4052.50	973.08
Penalty Cost[e]	Average Unit Cost × 1.5 × 1.5	
Inventory Holding Cost[f]	Average Unit Cost × 0.2	
Delivery Cost[g]	Average Unit Cost × 1.5 × 0.18	
Inventory Carrying Capacity[h]	Maximum = 2,000,000/52 Minimum (Safety Stock) = Maximum × 0.2	Maximum = Maximum of IC × 120% Minimum = Minimum of IC

d. Talluri et al. (2013)
e. We assume that material cost is 60-65% of the cost of finished goods; Penalty cost is 150% of unit revenue (unit revenue = 150% × Unit cost)
f. Inventory holding cost is calculated based on the value of raw material
g. http://www.smartgrowthamerica.org/complete-streets/complete-streets-fundamentals/factsheets/transportation-costs
h. We assume that initial maximum capacity is weekly production quantity and minimum capacity is one day production quantity under assumption that operating days per week is five days.

For expressing focal company's risk attitude, we run the model over a variety of weight sets (Table E1-4). The result shows that total reliability is increasing with a decreasing rate in total cost, i.e., a concave shaped curve. This result is consistent to the findings in Yildiz et al. (2015). The figure on the left in the Figure E1-4 is normalized results of all the 100 demand sets, while the figure on the right is averaged result of the

100 demand sets. The left one more clearly shows that the concave shape is still maintained at highly emphasized reliability cases. However, we utilize the right one in further analysis, since it illustrates the results more simply.

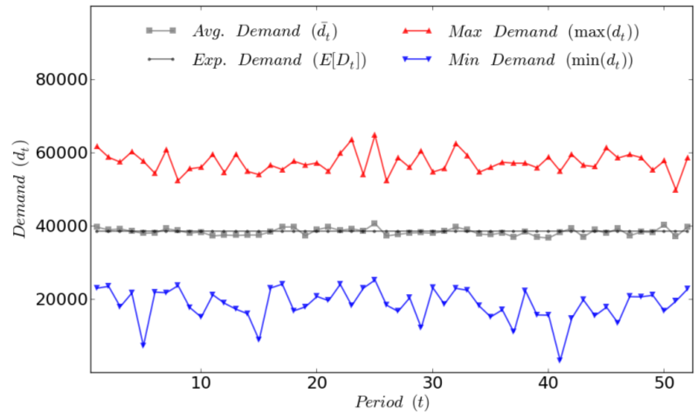

Figure E1-3: Simulated demand information over planning period

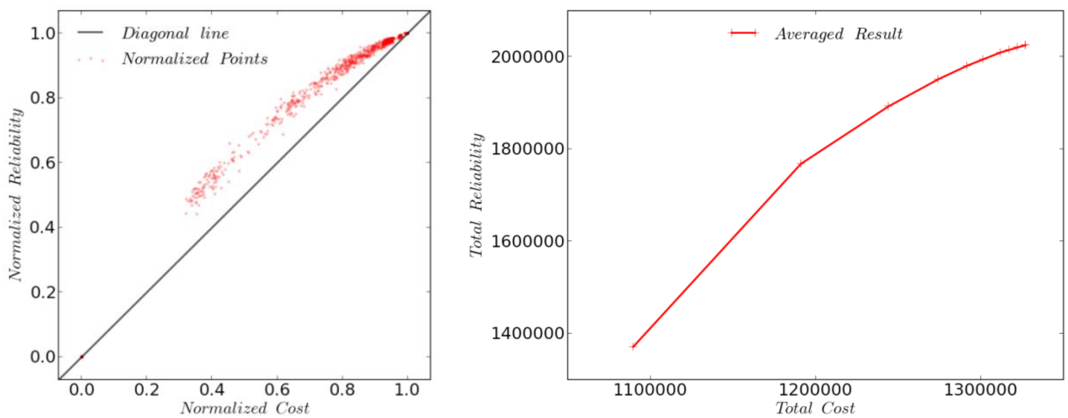

Figure E1-4: Base MOMIP results (Reference)

Table E1-4: Weight sets

	Cost Only	**Set 1**	**Set 2**	**Set 3**	**Set 4**	**Set 5**	**Set 6**	**Set 7**	**Set 8**	**Set 9**	**Rel. Only**
$\boldsymbol{\omega_C}$	1.0	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0.0
$\boldsymbol{\omega_R}$	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0

The result indicates that even a small emphasis placed on supply chain reliability (Set 1 in Table E1-4) makes a big difference in the solution compared to the case that only considers cost (Cost Only in Table E1-4). In this range, a large improvement in reliability is achieved with a relatively low increase in total cost. However, the effectiveness (on reliability improvement) of the spending is decreasing (the slope of the curve is decreasing as the ratio of ω_C to ω_R decreases. The base model is constrained by single sourcing, which means that this model reduces risk (increase reliability) only through changing sourcing quantity, supply amount to the customer, and inventory level. The next set of figures show the effects of risk mitigation strategies with sole strategy selection.

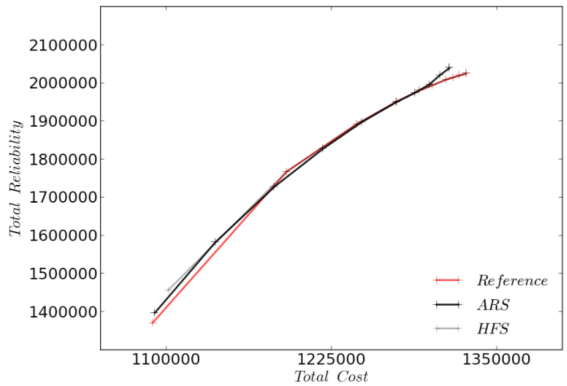

Figure E1-5.1: Upstream risk mitigations

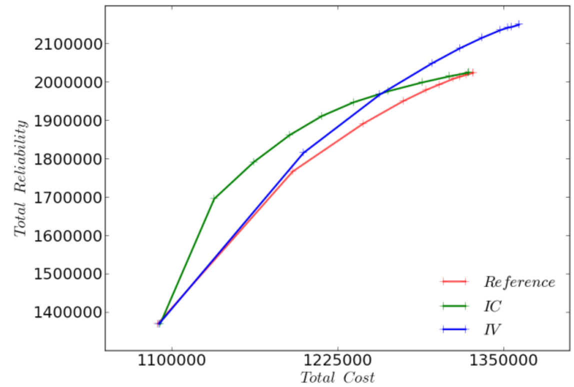

Figure E1-5.2: Downstream risk mitigations

With the parameter set and demand data used, upstream risk mitigation strategies do not seem to result in much improvement over the reference results with no mitigation strategy used (Figure E1-5.1), while downstream risk mitigation strategies improve the focal company's performance in both cost and risk. It is because the focal company's (manufacturing) capacity is tight (i.e., manufacturing capacity is equal to the expected demand). Thus, increase sourcing ability from the dual sourcing (ARS) does not increase focal company's performance over all the weight sets. Moreover, the tight capacity enforces the focal company sources redundant quantities, which means that volume flexibility (HFS) can increase a little bit of performance when the focal company's risk attitude is risk taking, but it does not increase the performance significantly as the attitude becomes more risk averse.

In Figure E1-5.2, we can initially confirm our first conjecture that the best strategy can vary depending on focal company's risk attitude. The IC is better strategy when the focal company's risk attitude is risk taking and risk neutral. However, IV becomes the better strategy when the focal company's risk attitude is risk averse. It is also because of the tight capacity. The increased (manufacturing) capacity (IC) enables the focal company can reduce lost sales (increase demand satisfaction). This can reduce cost and at the same time increase reliability, when focal company's risk attitude is not risk averse. However, this positive effect is attenuated as the risk attitude becomes more risk averse, since the focal company will source more quantity and deliver more quantity under this attitude even in the base (reference) case. This behavior in the reference can be strengthened with IV so that the performance under the attitude of high risk averse can be increased.

Figure E1-6.1 shows that the mixed strategy (ARS + IC) results in superior performance compared to the individual strategies (ARS only and IC only). This result can be interpreted as an indicator of the importance of alignment between the individual strategies in a mixed strategy in the following way: Since the capacity of the focal company is tight (i.e., expected demand is equal to capacity), the capacity increase (IC) allows the company to utilize the increased sourcing amount achieved from the dual sourcing (ARS). In Figure E1-6.2, the mixed strategy does not result in a similar improvement over the individual strategies since there is not an alignment between these strategies: With the increased inventory capacity (IV) and increased sourcing capability (ARS), although the focal company can store more inventory, it cannot increase its delivery of finished products at the same level due to constrained production capacity, which limits its ability to increase the total reliability.

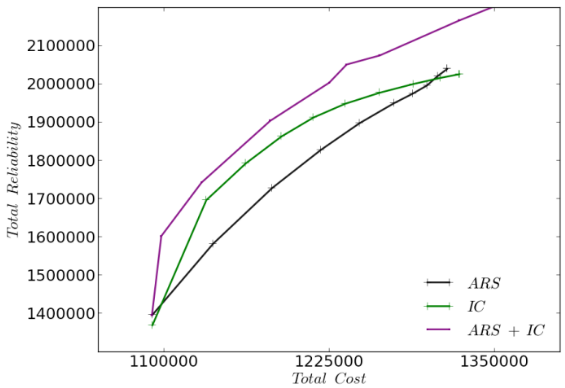

Figure E1-6.1: ARS + IC

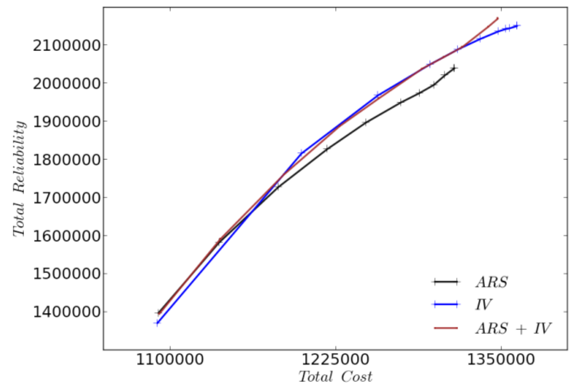

Figure E1-6.2: ARS + IV

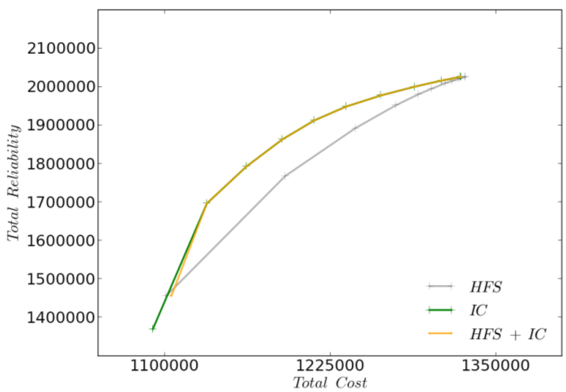

Figure E1-6.3: HFS + IC

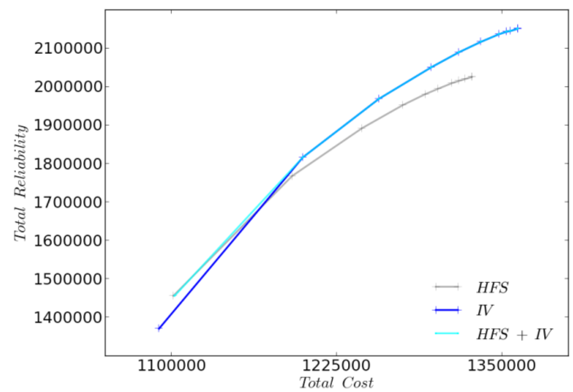

Figure E1-6.4: HFS + IV

Similar results are obtained in Figures E1-6.3 and E1-6.4, which show that the combinations of HFS and downstream risk mitigation strategies (IC and IV) do not improve the risk mitigation performance compared to the better performance achieved among the sole strategies. In other words, the mixture of HFS and IC does not significantly outperform IC only strategy (the better strategy among HFS only and IC only). The increased focal company capacity (IC) increases the total reliability by increasing supply amount to the customer and avoids shortage costs. To achieve this effect, the focal company sources some redundant amount from the supplier. Thus, the flexibility in supply side does not improve the performance of IC only. Similarly, IV mitigates risk by increasing inventory level. Thus, this strategy leads the focal company to source some redundant amount from the supplier. Therefore, the increased flexibility (HFS) does not significantly increase the efficiency of the use of IV only.

6. Conclusions and Extensions

In this article, we initially expected that different risk attitudes will select different risk mitigation strategies. Regarding this expectation, we applied multi objective concept in our analysis. The results confirm this expectation. Moreover, we simultaneously address the issue of supplier selection during a given planning horizon in a supply chain and a consideration of risk mitigation strategy selection with the argument that *risk mitigation should be considered at the supplier selection phase with the mixture of upstream and downstream risk mitigation strategies rather than separately applying a sole strategy*. The results show that the simultaneous consideration of upstream and downstream risk mitigation strategies has the potential for better performance than separately using each strategy. However, the mixed strategies do not guarantee that they outperform individual strategies, which means that the alignment between the strategies in a mixture is critical for better performance.

We consider only four different strategies including two upstream and two downstream strategies. However, there are other risk mitigation strategies developed in literature. Therefore, an extension of this study could be deriving more well-aligned mixed strategies by considering combinations of more mitigation strategies.

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ESSAY 2

OPTIMAL SOURCING DECISIONS AND INFORMATION SHARING UNDER MULTI-TIER DISRUPTION RISK IN A SUPPLY CHAIN

Abstract

This paper considers a manufacturer's sourcing decision in a three-tier supply chain under disruption risk. The manufacturer sources identical and critical components from a single first-tier supplier (FT). The FT in turn sources identical and critical raw materials from a single second-tier supplier (ST). The suppliers in both tiers are unreliable, i.e., prone to disruption risk, and supplier diversification is not an available option. In this situation, increasing supply chain visibility through information sharing is a potential disruption management strategy for the manufacturer. While the manufacturer can easily obtain disruption-risk information for the FT, disruption risk information for the ST is not easily accessible to the manufacturer. Instead, the manufacturer must gather ST disruption risk information via the FT (i.e., sequential information sharing). However, the FT may not be willing to share ST information. We study different mechanisms under which the manufacturer can obtain ST information, and how this information impacts not only manufacturer's but also FT's decisions and potential profits. We show that information sharing makes the manufacturer's sourcing decision more conservative but the FT's sourcing decision more proactive. We demonstrate that there are three ways to induce the FT to share its information, and numerically show that their effectiveness is contingent on multiple factors including FT and ST reliabilities and information sharing costs.

1. Introduction

A massive Tsunami hit Tōhoku, Japan, on March 11, 2011. As a result, many companies, particularly in the automotive industry, faced supply chain disruptions. Toyota Motor Corporation (hereafter referred to as Toyota) was one of the companies affected by the recent Tsunami. Before the Tsunami, Toyota had a diverse pool of first-tier suppliers (FT) for most of the parts and components which it purchased hedging against supply chain disruptions. However, for some components, Toyota had to heavily rely on either one or very few FTs because of geographical and/or technological restrictions (McVeigh, 2011[3]). Given these restrictions in the automotive industry, it is not uncommon for FT suppliers to rely on a very limited number of ST suppliers. The Japan Tsunami disrupted the operations of some of Toyota's FTs as well as STs, and, as a result, inhibited Toyota's ability to respond to the resulting supply chain disruption (Toyota Annual Report 2011[4]).

"Before the disaster, we knew about our FTs but we didn't know about our second, third or fourth tier suppliers," said Masami Doi, Head of the Public Affairs Division at Toyota (Novotny, 2012[5]). Prior to the disaster, Toyota had focused mostly on its FTs. The 2011 disaster highlighted the importance of managing higher tiers in the supply chain in order to reduce the risk and impact of supply chain disruptions. One way companies can reduce the risk and impact of disruptions is by increasing information sharing among the different tiers in the supply chain. Masami Doi mentioned that "Since the quake, we are trying to be able to visualize everything, including these third and fourth

[3] http://europe.autonews.com/article/20110701/ANE/110709998/single-sourcing-risks-highlighted-after-japan-earthquake
[4] http://www.toyota-global.com/investors/ir_library/annual/pdf/2011/p35_37.pdf
[5] http://www.industryweek.com/planning-amp-forecasting/japan-manufacturers-post-tsunami-rethink

tiers” (Novotny, 2012). Nevertheless, the process of sharing information is not always easy. In the case of Toyota, approximately 50% of FTs were unwilling to share information regarding STs with Toyota (Ang et al., 2014).

Motivated by this and other similar events such as the 2011 Thailand floods that caused major disruptions to the electronic manufacturing industry, in this paper, we consider the problem of optimal sourcing decisions when disruptions may occur not only in the FT, but also in the ST. Specifically, we examine a stylized model in which a manufacturer sources a critical component from a single FT. The FT in turn sources a critical raw material from a single ST. We consider a two-period model where disruptions can occur in period 2. We assume that the manufacturer and FT can directly estimate the likelihood of disruption, or disruption risk, of its immediate supplier. Therefore, the manufacturer can estimate the FT disruption risk, while the FT can estimate the ST disruption risk. The manufacturer can gather ST disruption risk information only through its FT, i.e., sequential information sharing. The manufacturer is interested in obtaining information on ST reliability and the inventory level of FT. ST reliability is critical for the manufacturer’s optimal sourcing decisions, since FT reliability may be overestimated if information related to ST is not considered. In addition, FT’s inventory level information is critical for the manufacturer, since inventory can mitigate the negative impact of ST disruption on FT reliability.

However, the immediate supplier (FT) may not be willing to share ST information. FT suppliers may experience concern that sharing ST information with manufacturer may affect the strength of the relationship between FT and ST if the manufacturer decides to get involved in sourcing decisions (Ang et al., 2014). This is particularly prevalent in industries where power asymmetry is common and powerful manufacturers typically influence FT purchasing practices (Maloni and Benton, 2000). In such a situation, we test three different mechanisms through which the manufacturer can provide the FT with incentives to obtain information. The three mechanisms considered are information buying (*IB*), semi-information swapping (*SIS*), and full information swapping (*FIS*).

Using our stylized model and the three incentive mechanisms tested (*IB*, *SIS*, and *FIS*), we seek to answer the following questions:

- How should the manufacturer's sourcing decisions be modified in the presence of ST disruption risk? Furthermore, how are these sourcing decisions different under the different information sharing mechanisms considered?
- What is the effect of information sharing on the FT's sourcing decisions?
- Can the different information sharing mechanisms considered increase not only the manufacturer's but also the FT's profits? If so, what conditions make one mechanism better than the others, and why?

In our model, we characterize the manufacturer's sourcing behavior when disruption risk is considered in both FT and ST. We show that the manufacturer's optimal sourcing decision becomes more conservative when gathering upstream information, i.e., the manufacturer will be more likely to purchase more in the first period, while the FT's sourcing strategy becomes more proactive, i.e., the FT will reduce inventory levels under information sharing. In addition, we numerically demonstrate that the benefits of information sharing for the manufacturer and FT are contingent on multiple factors especially FT and ST reliabilities and information sharing costs.

The rest of the paper is structured as follows. In Section 2, a review of current literature is presented. Section 3 focuses on the general model description. Section 3.1 describes the optimal manufacturer's sourcing decisions considering only FT disruption risk and Section 3.2 depicts both FT and ST disruption risk, using different information sharing mechanisms. In Section 3.3, we study the FT's behavior under information sharing as well as non-information sharing. In Section 4, we numerically experiment the effectiveness of the three information sharing mechanisms explored. Finally, Section 5 presents a summary of the main contributions and future extensions of the paper.

2. Literature Review

Supply chain risk management (SCRM) is a relatively new area of study. Nevertheless, it has attracted significant attention as can be seen by the growing number of research articles published in recent years (Tang, 2006). In the past, most businesses did not consider disruption risk when planning their operations, nevertheless, this trend is changing. In the early stages of SCRM literature, risk was addressed mainly in the context of manufacturing processes experiencing risk through demand uncertainty, lead-time uncertainties, and random yields in production or procurement (e.g., Zipkin, 2000). Vast literature considers safety stocks and warehouses between manufacturers and retailers as a means to reduce the effect of demand and lead-time uncertainties (Diks et al., 1996; Van Houtum et al., 1996; Schwarz and Weng, 2000). Research that explores the impact of random yields in production or procurement, where the level of production or supply is determined by a random function of the input level, includes the work of Yano and Lee (1995), Gurnani et al. (2000), Grosfeld-Nir and Gerchak (2004), and He and Zhang (2008). In addition, an increased interest in how companies should prepare in the case of catastrophic events led to the work by Martha and Vratimos (2002), Simchi-Levi et al. (2004), and Chopra and Sodhi (2004) among others.

As the academic interest began to grow in the area of SCRM, the importance of considering external providers and their impact on supply chain vulnerability was studied by several authors. Klibi et al. (2010) emphasizes the criticality of disruption risk of upstream supply chain members in a supply chain. Davis (1993) argues that suppliers' performance plays a prominent role in the efficiency of a supply chain. Li and Cheng (2010) also point out that upstream disruption risk is the most severe factor that threatens supply chain continuity. Recent unexpected tragic events, (e.g., 911 terror attacks in 2001, 2011 Tōhoku earthquake and tsunami, and 2011 Thailand floods) have stimulated both academia and practitioners to pay attention to disruption management in the supply chain (e.g., Snyder et al., 2010).

The existing disruption management literature has focused on supplier diversification as a possible means to mitigate risk. Sheffi (2001) introduces dual supply arrangements in strategic supply chain design and provides illustrative analytical formulations for network design under disruption risk. The work of Tomlin and Wang (2005) examines the effect of single versus dual sourcing on supply chain performance under disruption risk. They demonstrate that the preference of dual sourcing increases as supply chain reliability decreases. Bernstein et al. (2013) also consider single versus multiple sourcing under disruption risk and show that diversification is not always the best strategy in risk management. Tomlin (2006) analytically presents a generalized supply chain design model by focusing on sourcing strategies (i.e., single, dual, or back-up sourcing) with consideration of disruptions under two different supplier settings: one is perfectly reliable but expensive and the second being unreliable but cheaper. Chopra et al. (2007) study back-up supply. They utilize the same dual supplier setting (reliable and unreliable) and provide an analytical model while considering disruption risks as well as recurrent risks that cause random yield. Hu and Kostamis (2015) study a manufacturer's optimal sourcing strategy when some suppliers may face disruption risk. Using an approximate model the authors show that the optimal orders placed to unreliable suppliers are ranked based on a cost-advantage-to-risk ratio. Yildiz et al. (2015) consider reliable supply chain network design problem and demonstrate that dual sourcing can be an effective strategy for improving reliability.

In addition to the literature exploring different sourcing strategies when faced with FT disruption risk as discussed above, recent research has also shown the importance of considering ST disruption risk (e.g., Zsidisin, 2003; Kull and Closs, 2007). Although the importance of considering ST disruption risk is recognized in both academia and practice, the related literature in this domain is sparse. To the best of our knowledge, Ang et al. (2014) is the only paper that explores disruption management in a multi-tier supply chain setting. They consider ST disruption risk in examining a manufacturer's sourcing decision. However, they assume a reliable FT and ignore FT disruption risk. They emphasize the supply correlation between FTs through their common STs, when diversification strategy is available.

However, in practice, the diversification strategy is not always feasible due to factors such as quality requirements, technological needs, or geographical restrictions. Under this setting, increasing supply chain visibility through information sharing can be an alternative strategy. While a vast amount of research has emphasized the importance of information sharing in the supply chain (e.g., Lee et al., 1997; Lee, 2000; Lee et al., 2000; Yu et al., 2001), to the best of our knowledge, there is no research that considers supplier's information sharing beyond the FT.

Our work differs from current literature as we simultaneously explore FT and ST disruption risk. In addition, our paper is the first to examine the value of higher-tier supplier information and consider its impact on both manufacturer's and FT's sourcing decisions. Furthermore, we investigate the effect of information sharing on profits by defining three different information sharing mechanisms.

3. Model

We consider a three-tier supply chain consisting of a single ST providing a critical raw material to a single FT. The FT transforms the raw materials and sells them as critical components to a single manufacturer who then produces finished products that are sold to the end customers as depicted in Figure E2-1. Without loss of generality, we assume that the FT and the manufacturer require one unit of raw material and one unit of the component to produce one unit of finished product (Zimmer, 2002). The manufacturer purchases components from the FT at price p, and sells finished products at price v. We assume there are no alternative FT and ST in this setting (Arreola-Risa and De Croix, 1998). We further assume that any excess inventories will be salvaged at their respective locations (at manufacturer or FT).

We consider a two-period model. Demand for finished products occurs only at the lowest echelon (final customer in Figure E2-1) in the supply chain. In anticipation of future demand, and in order to hedge against supply uncertainty in period 2, the manufacturer and the FT may carry inventory from one period to the next.

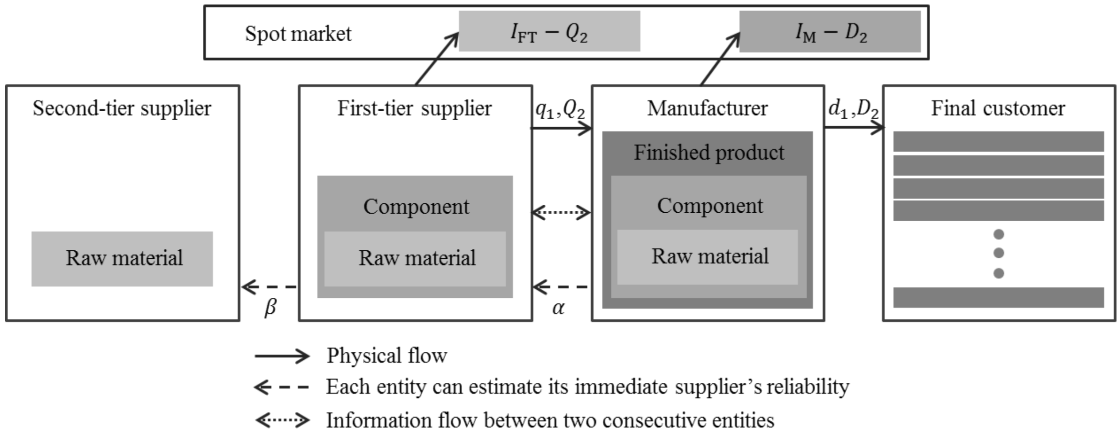


Figure E2-1: Basic supply chain setting

The manufacturer can sell at most d_1 and D_2 units of finished product to its customers in period 1 and 2, respectively, (we assume that the manufacturer knows d_1, while D_2 is unknown and normally distributed with mean μ and variance σ_{M}^2) but may purchase more than d_1 units of component from the FT (i.e., $d_1 + I_{\mathrm{M}} = q_1 \geq d_1$) in period 1 (note that subscript M represents the manufacturer). We assume the FT's capacity is high enough to cover the manufacturer's total ordering quantity (q_1) in period 1, $d_1 + I_{\mathrm{M}}$, where I_{M} is manufacturer's inventory level. In period 2, however, the FT may experience a disruption with probability $(1 - \alpha)$; hence the FT delivers either the full quantity the manufacturer orders with probability α, or zero with probability $(1 - \alpha)$ (Yano and Lee, 1995; Aydin et al., 2010; Ang et al., 2014). As is common in the supply chain literature (Snyder et al., 2010), a supplier's status is either "UP" or "DOWN". Where "UP" means orders are fulfilled in full and on time, and "DOWN" means orders cannot be fulfilled. In anticipation of a supply chain disruption, the manufacturer has the option of preordering I_{M} units of inventory in period 1 to satisfy demand for period 2. Nevertheless, any inventory carried from period 1 to period 2 incurs a unit holding cost $p \cdot h_{\mathrm{M}}$, where p is the FT's selling price of the component and h_{M} is the inventory holding cost rate, $0 < h_{\mathrm{M}} < 1$. Note that

Q_2 is the manufacturer's order quantity in period 2. We assume that there is no initial inventory and no backorders, and any unmet demand is lost.

In addition to potential disruptions at the FT level, the ST may also experience a disruption with probability $(1-\beta)$. In order to hedge against ST disruption risk, FT may hold inventory (as raw material). In case ST is disrupted, FT will try to satisfy the manufacturer's demand using available inventory.

3.1. Manufacturer's Optimal Behavior without Upstream Information

The manufacturer will have an incentive to purchase components from FT whenever profitable, i.e. $v \geq p$. Given the possibility of FT's disruption in period 2, the manufacturer will have an incentive to preorder certain amount of inventory in period 1, I_{M}, whenever the expected profit from preordering inventory exceeds the inventory holding cost.

We can estimate the manufacturer's profit π_{M} as:

$$\pi_{\mathrm{M}} = \begin{cases} \pi_{\mathrm{M}}^{\mathrm{up}}, \text{ if FT is not disrupted (Up)} \\ \pi_{\mathrm{M}}^{\mathrm{dn}}, \text{ if FT is disrupted (Down)} \end{cases} \tag{1}$$

, where

$$\pi_{\mathrm{M}}^{\mathrm{up}} = v(d_1 + D_2) - p(d_1 + I_{\mathrm{M}}) - ph_{\mathrm{M}}I_{\mathrm{M}} - p(D_2 - I_{\mathrm{M}})^+ + s(I_{\mathrm{M}} - D_2)^+$$

$$\pi_{\mathrm{M}}^{\mathrm{dn}} = v(d_1 + D_2) - p(d_1 + I_{\mathrm{M}}) - ph_{\mathrm{M}}I_{\mathrm{M}} - v(D_2 - I_{\mathrm{M}})^+ + p(I_{\mathrm{M}} - D_2)^+$$

This yields an expected profit for the manufacturer over two periods of

$$\begin{aligned} \mathrm{E}[\pi_{\mathrm{M}}] = (v-p)d_1 &- \big(v - (\alpha s + (1-\alpha)p)\big)\mu \\ &- \big((1+h_{\mathrm{M}})p - (\alpha s + (1-\alpha)p)\big)I_{\mathrm{M}} \\ &- \big(\alpha(p-s) + (1-\alpha)(v-p)\big)\int_{I_{\mathrm{M}}}^{\infty}(t - I_{\mathrm{M}})\,dF(t) \end{aligned} \tag{2}$$

- Notation:

v	:	Manufacturer's unit selling price of finished good
p	:	FT's unit selling price of component (manufacturer's unit buying price of component)
s	:	Manufacturer's unit salvage value
h_{M}	:	Manufacturer's unit inventory holding cost rate
α	:	FT reliability (estimated by the manufacturer)
d_1	:	Deterministic demand of period 1
D_2	:	Stochastic demand of period 2, $D_2 \sim N(\mu, \sigma_{\mathrm{M}}^2)$
I_{M}	:	Manufacturer's preorder quantity (manufacturer's inventory level)

The manufacturer's optimal order size in period one when FT disruption risk is considered is described in Proposition 1.

Proposition 1. In the presence of FT disruption risk, the preorder quantity I_{M}^* placed in period 1 (ignoring ST disruption) is given by

$$I_{\mathrm{M}}^* = \max\left(0, \sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{(h_{\mathrm{M}} + \alpha)p - \alpha s}{\alpha(p-s) + (1-\alpha)(v-p)}\right) + \mu\right). \tag{3}$$

, where $G(z)$ is the standard normal cumulative distribution. Proof for Proposition 1 is included in Appendix A. Proposition 1 indicates that when the manufacturer's unit selling price v becomes high relative to the FT's unit selling price p, the manufacturer will preorder more for hedging against disruption risk. Moreover, as the upstream disruption likelihood, $(1-\alpha)$, increases the preorder quantity also increases in order to mitigate the negative impact of upstream disruption. This proposition further tells us that when the ratio of manufacturer's unit selling price to FT's unit selling price, $\frac{v}{p}$, is low, the manufacturer will not carry inventory, i.e., $\frac{v}{p} < \frac{1+h_{\mathrm{M}}-\alpha}{1-\alpha}$ (refer to proof in Appendix A). In addition, this ratio determines the manufacturer's behavior in the presence of increased demand variability. As shown in Appendix A, if $\frac{v}{p} < (>) \frac{2(1+h_M)-\alpha}{1-\alpha}$ the manufacturer will order less (more) inventory as the demand variability increases.

3.2. Manufacturer's Optimal Behavior under Information Sharing Contract

In Section 3.1, ST disruption risk is ignored, i.e., the model assumes that FT can always satisfy the manufacturer's demand if FT is UP. However, if the ST is DOWN in period 2, then FT may not be able to satisfy the manufacturer's full demand in period 2, even though FT is UP. In this case, FT can only satisfy the manufacturer's demand from available inventory. Thus, the manufacturer's demand in period 2 may not be fully satisfied.

Table E2-1: Different information sharing contract mechanisms

Mechanism Type	Info. Flow	Description
Type 1 Information Buying **(*IB*)**	Uni-directional Info. Sharing	The manufacturer buys upstream information including ST's disruption likelihood and FT's inventory level from the FT at higher cost
Type 2 Semi-information Sharing **(*SIS*)**	Bi-directional Info. Sharing	The manufacturer buys the upstream information from the FT at lower cost but provides a part of downstream information (final demand) to the FT
Type 3 Full-information Sharing **(*FIS*)**	Bi-directional Info. Sharing	The manufacturer and the FT share upstream information (ST's disruption likelihood and FT's inventory level) and downstream information (final demand and the manufacturer's inventory level) at very low cost

The manufacturer can estimate its new profit function if information on both ST disruption likelihood and FT's inventory level are accessible. Nevertheless as mentioned earlier, FT may not be willing to share information regarding ST disruption risk or inventory levels. The manufacturer therefore needs to provide the FT incentives in order to obtain the desired information. We test three different incentive mechanisms: information buying (*IB*), semi-information sharing (*SIS*), and full-information sharing (*FIS*) (see Table E2-1 above).

Under the information buying mechanism (*IB*), the manufacturer offers an information sharing contract with high rewards in exchange for ST disruption information. The reward offered by the manufacturer is proportional to the amount of inventory the FT keeps at the end of period 1. The manufacturer offers to reward the FT in full for its inventory holding costs. However, if the FT finds the contract conditions to be favorable, it may opt to keep too much inventory; thus, the manufacturer will impose an upper bound (*UB*) on the amount of inventory that it is willing to compensate for. While the manufacturer may or may not purchase the entire inventory held by FT, in case of ST disruption, FT is expected to satisfy the manufacturer's order of components up to *UB*. In case FT fails to supply the manufacturer's demand in period 2, it should compensate the manufacturer's loss from supply shortage up to *UB*.

From FT's perspective, final demand information is critical (Lee et al., 1997). Thus, in the semi-information sharing mechanism (*SIS*), the manufacturer offers an information sharing contract with relatively lower rewards (compared to the rewards in *IB* corresponding to full reward of inventory holding costs) for the manufacturer's desired FT's inventory level and upstream information (ST's disruption likelihood), but provides final demand information to FT. The obligations and advantages of the *SIS* contract are similar to those of *IB* contract. Additionally, manufacturer's inventory level plays a critical role in FT's sourcing decisions. Under the full-information sharing mechanism (*FIS*), the manufacturer offers a very low reward (compared to the reward under *IB* and *SIS*), but exchanges final demand and inventory level information with the FT. The obligations and advantages of the *FIS* contract are similar to those of the *IB* contract.

We now derive profit expressions for the manufacturer under the different information sharing contracts considered.

We use $(I_{\mathrm{MF}})_n$ and $\mathcal{C}_n = p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})(I_{\mathrm{MF}})_n$ to denote respectively, the manufacturer's desired ending inventory of raw material at FT in period 1, and the upstream information sharing cost paid by the manufacturer under information sharing mechanism n, $n = \{1, 2, 3\}$. Where 1, 2, and 3 represent *IB*, *SIS*, and *FIS*, contracts, respectively; k_n represents the portion of FT inventory holding cost paid by manufacturer under mechanism n, and h_{FT} represents the unit inventory holding cost rate on FT. By slightly modifying expression (1), the profit when the FT is down can be expressed as $\left(\pi_{\mathrm{M}}^{\mathrm{dn}}\right)_n = \pi_{\mathrm{M}}^{\mathrm{dn}} - \mathcal{C}_n$; the profit when the FT is up is denoted as $\left(\pi_{\mathrm{M}}^{\mathrm{up}}\right)_n$,

$$\left(\pi_{\mathrm{M}}^{\mathrm{up}}\right)_n = \begin{cases} v(d_1 + D_2) - p(d_1 + (I_{\mathrm{M}})_n) - ph_{\mathrm{M}}(I_{\mathrm{M}})_n - p(D_2 - (I_{\mathrm{M}})_n)^+ \\ \qquad +s((I_{\mathrm{M}})_n - D_2)^+ - \mathcal{C}_n\ , & \text{if the ST is Up} \\ v(d_1 + D_2) - p(d_1 + (I_{\mathrm{M}})_n) - ph_{\mathrm{M}}(I_{\mathrm{M}})_n - v(D_2 - (I_{\mathrm{M}})_n - (I_{\mathrm{MF}})_n)^+ \\ \qquad -p((I_{\mathrm{MF}})_n + (D_2 - (I_{\mathrm{M}})_n - (I_{\mathrm{MF}})_n)^-) - \mathcal{C}_n\ , & \text{if the ST is Down} \end{cases} \tag{4}$$

p_{ST}	:	ST's unit selling price of raw material (FT's unit buying price of raw material)
h_{FT}	:	Unit inventory holding cost rate on FT
β	:	ST reliability (estimated by FT)
$(I_{\mathrm{M}})_n$	:	Manufacturer's inventory under mechanism n
$(I_{\mathrm{MF}})_n$	:	Manufacture's desired FT inventory under mechanism n
k_n	:	Portion of FT inventory holding cost paid by manufacturer under mechanism n, $k_1 = 1$ and $k_1 > k_2 > k_3 > 0$

Based on the different contract mechanisms considered, *IB*, *SIS*, and *FIS*; the expected profit for the manufacturer is given by:

$$\begin{aligned}\mathrm{E}[(\pi_{\mathrm{M}})_n] = {} & v(d_1+\mu) - p(d_1+(I_{\mathrm{M}})_n) - ph_{\mathrm{M}}(I_{\mathrm{M}})_n \\ & - (\alpha(1-\beta)p + (1-\alpha)p + \alpha\beta s)(\mu - (I_{\mathrm{M}})_n) \\ & - (\alpha\beta p + (1-\alpha)v - (1-\alpha)p - \alpha\beta s)\int_{(I_{\mathrm{M}})_n}^{\infty}(t-(I_{\mathrm{M}})_n)\,dF(t) \\ & - \alpha(1-\beta)(v-p)\int_{(I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n}^{\infty}\big(t-((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)\big)\,dF(t) \\ & - \mathcal{C}_n\end{aligned} \tag{5}$$

, where $\mathcal{C}_n = p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})(I_{\mathrm{MF}})_n$. We assume that the unit inventory cost of raw materials is lower than that of the components, i.e., $p_{\mathrm{ST}}h_{\mathrm{FT}} \le ph_{\mathrm{M}}$.

Proposition 2. When the manufacturer pays upstream information sharing cost to FT, the manufacturer's optimal preorder quantity $(I_{\mathrm{M}}^*)_n$ and the manufacturer's desired inventory level, $(I_{\mathrm{MF}}^*)_n$, at FT in period 1 under mechanism n are given by:

$$\begin{aligned}(I_{\mathrm{M}}^*)_n &= \max\left(0, \sigma_{\mathrm{M}}G^{-1}\left(1-\tfrac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)}\right)+\mu\right) \text{ and} \\ (I_{\mathrm{MF}}^*)_n &= \sigma_{\mathrm{M}}G^{-1}\left(1-\tfrac{p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}\right)+\mu-(I_{\mathrm{M}}^*)_n, \text{ respectively.}\end{aligned} \tag{6-1}$$

These expressions hold if $(I_{\mathrm{M}}^*)_n > 0$ and $p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}}) < \delta\big((h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s\big)(\gamma+\delta)^{-1}$, or if $(I_{\mathrm{M}}^*)_n = 0$ and $p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}}) < \delta$; where $\delta = \alpha(1-\beta)(v-p)$ (>0) and $\gamma = \alpha\beta(p-s)+(1-\alpha)(v-p)$ (>0).

Otherwise, the optimal solutions are given by:

$$\begin{aligned}(I_{\mathrm{M}}^*)_n &= \max\left(0, \sigma_{\mathrm{M}}G^{-1}\left(1-\tfrac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s}{\alpha\beta(p-s)+(1-\alpha\beta)(v-p)}\right)+\mu\right) \text{ and } (I_{\mathrm{MF}}^*)_n \\ &= 0, \text{ respectively,}\end{aligned} \tag{6-2}$$

Proof for Proposition 2 is included in Appendix B.

Propositions 1 and 2 enable us to examine the manufacturer's optimal sourcing decision with and without information sharing mechanisms. Figures E2-2 and E2-3 show how the manufacturer's decisions under an *IB* contract ($n = 1$), compare to those without information sharing. Note that from the manufacturer's perspective, the only factor that makes a difference in the its optimal sourcing decision among the three different mechanisms is k_n, the portion of FT inventory holding cost paid for by the manufacturer under mechanism n. The overall shapes of $(I^*_{\mathrm{M}})_n$ and $(I^*_{\mathrm{MF}})_n$ curves will not change with $n = 1, 2$, or 3. However, $(I^*_{\mathrm{M}})_1 > (I^*_{\mathrm{M}})_2 > (I^*_{\mathrm{M}})_3$ and $(I^*_{\mathrm{MF}})_1 < (I^*_{\mathrm{MF}})_2 < (I^*_{\mathrm{MF}})_3$, since, by definition, $k_1 > k_2 > k_3$ and $G^{-1}(\cdot)$ is monotone increasing.

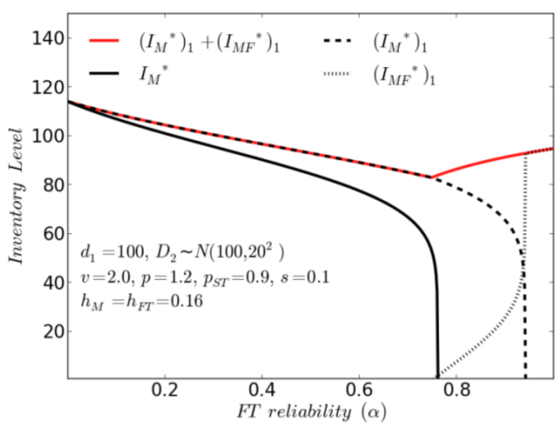


Figure E2-2: Inventory levels vs. FT reliability at $\boldsymbol{\beta} = 0.7$

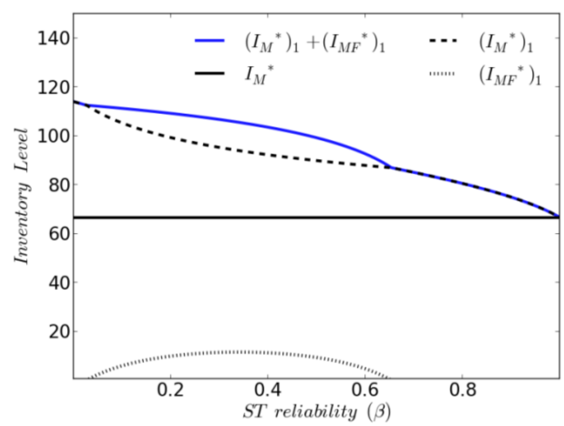


Figure E2-3: Inventory levels vs. ST reliability at $\boldsymbol{\alpha} = 0.7$

Proposition 3. For a given set of parameters, the manufacturer preorders more component units under upstream information sharing, i.e., $(I^*_{\mathrm{M}})_n \geq I^*_{\mathrm{M}}$.

Proof for Proposition 3 is included in Appendix C.

Proposition 3 indicates that considering ST disruption makes the manufacturer's sourcing decision more conservative because $\beta \leq 1$. Therefore, FT reliability α does not fully determine the likelihood of demand satisfaction in period 2; the likelihood that FT will be able to satisfy demand fully in period 2 is less than α. If FT is absolutely unreliable, i.e., $\alpha = 0$, the manufacturer will preorder all the units required for the following period in period 1 regardless of ST disruption risk. Moreover, if ST is perfectly reliable, i.e., $\beta = 1$, the impact of ST disruption becomes zero. Thus, Figures E2-2 and E2-3 show that as $\alpha \to 0$ or $\beta \to 1$; $(I_{\mathrm{M}}^*)_n \to I_{\mathrm{M}}^*$; $(I_{\mathrm{M}}^*)_1$ converges to I_{M}^* as α decreases to zero in Figure E2-2 and as β increases to one in Figure E2-3. Moreover, in both figures, $(I_{\mathrm{M}}^*)_1$ is never less than I_{M}^* over all the ranges of α and β.

Proposition 4. For a given set of parameters, i) the manufacturer increases component inventory level $(I_{\mathrm{M}}^*)_n$ as the FT (ST) disruption likelihood $1 - \alpha$ $(1 - \beta)$ increases. ii) It is guaranteed that $(I_{\mathrm{MF}}^*)_n$ is always decreasing as $1 - \alpha$ increases, but $(I_{\mathrm{MF}}^*)_n$ can be increasing or decreasing as $1 - \beta$ increases. Moreover, the joint inventory, i.e., $(I_{\mathrm{M}}^*)_n + (I_{\mathrm{MF}}^*)_n$ is increasing (decreasing) as $1 - \alpha$ increases when $(I_{\mathrm{MF}}^*)_n = 0$ $((I_{\mathrm{MF}}^*)_n > 0)$ but is always increasing in $1 - \beta$.

Proof for Proposition 4 is included in Appendix D. Proposition 4 implies that as the FT becomes more reliable, the manufacturer will try to reduce total inventory holding costs (the sum of inventory costs at the manufacturer's and FT's facilities) by stocking more raw materials at FT and stocking less components at its own site, since unit inventory holding cost of raw materials is cheaper than the unit inventory holding cost of components. Moreover, the high reliability of FT provides the manufacturer with more opportunities to utilize the raw material inventory carried at FT when the ST is disrupted. However, the sum of component and raw material inventory increases as FT reliability increases. The amount of inventory at FT increases by taking advantage of low inventory holding cost and ordering postponement. On the other hand, an increase in ST reliability leads to lower levels of component but higher or lower raw material inventory at FT. It is interesting to note the impact of ST disruption risk on $(I_{\mathrm{MF}}^{*})_n$. Figure E2-3 illustrates that $(I_{\mathrm{MF}}^{*})_n$ has an inverted u- shaped relationship with ST reliability, i.e., initially increases and then decreases. The reason for this behavior is the following: when ST reliability is very low, the chance to use the inventory at FT level is highly dependent on FT reliability, i.e., $\alpha(1-\beta)$ is decreasing in β. Therefore, when FT reliability is not high enough, the manufacturer will prefer to stock more inventory at its own site rather than at FT. Thus, $(I_{\mathrm{MF}}^{*})_n$ increases at very low β range. However, it decreases from a certain β, since the increment of β (i.e., the decreased likelihood of ST disruption) represents that the chance to use the inventory at FT will decrease.

3.3. FT's Optimal Behavior in the Absence and Presence of Information Sharing Contracts

FT can sell $q_1 = d_1 + I_{\mathrm{M}}^{*}$ units to the manufacturer in period 1, but may purchase more than this amount of raw material from ST (i.e., $d_1 + I_{\mathrm{M}}^{*} + I_{\mathrm{FT}}$) in period 1. Each unit of unsold component has a unit holding cost, $h_{\mathrm{FT}} \cdot p_{\mathrm{ST}}$, at the FT level. We assume that the ST's capacity is high enough to cover FT's total ordering quantity in period 1, $d_1 + I_{\mathrm{M}}^{*} + I_{\mathrm{FT}}$. In period 2, however, FT's demand may not be satisfied due to ST disruption risk. We use $1-\beta$ to denote FT's anticipation of ST disruption likelihood in period 2.

We assume that the FT can forecast the final demand but has less accurate final demand information than the manufacturer, i.e., $Q_2 \sim N(\mu, {\sigma_{\mathrm{FT}}}^2)$, where $\sigma_{\mathrm{FT}} > \sigma_{\mathrm{M}}$. Based on these assumptions, FT's profit function, π_{FT}, before the use of information sharing contracts is as follows:

$$\pi_{\mathrm{FT}} = \begin{cases} \pi_{\mathrm{FT}}^{\mathrm{up}}, \text{ if ST is not disrupted (Up)} \\ \pi_{\mathrm{FT}}^{\mathrm{dn}}, \text{ if ST is disrupted (Down)} \end{cases} \tag{7}$$

, where

$$\pi_{\mathrm{FT}}^{\mathrm{up}} = p(d_1 + I_{\mathrm{M}}^* + Q_2) - p_{\mathrm{ST}}(d_1 + I_{\mathrm{M}}^* + I_{\mathrm{FT}}) - p_{\mathrm{ST}} h_{\mathrm{FT}} I_{\mathrm{FT}} - p_{\mathrm{ST}}(Q_2 - I_{\mathrm{FT}})^+ + s_{\mathrm{FT}}(I_{\mathrm{FT}} - Q_2)^+$$

$$\pi_{\mathrm{FT}}^{\mathrm{dn}} = p(d_1 + I_{\mathrm{M}}^* + Q_2) - p_{\mathrm{ST}}(d_1 + I_{\mathrm{M}}^* + I_{\mathrm{FT}}) - p_{\mathrm{ST}} h_{\mathrm{FT}} I_{\mathrm{FT}} - p(Q_2 - I_{\mathrm{FT}})^+ + p_{\mathrm{ST}}(I_{\mathrm{FT}} - Q_2)^+$$

Similar to the manufacturer's case, FT's optimal inventory level I_{FT}^* is defined as follows.

Proposition 5. In the presence of ST disruption, the preorder quantity under non-information sharing I_{FT}^* (raw material inventory level at FT) in period 1 is given by

$$I_{\mathrm{FT}}^* = \max\left(0, \sigma_{\mathrm{FT}} G^{-1}\left(1 - \frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}} - \beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}} - s_{\mathrm{FT}}) + (1-\beta)(p - p_{\mathrm{ST}})}\right) + \mu\right). \tag{8}$$

Proof for Proposition 5 is included in Appendix E.

FT's optimal inventory level changes under the different information sharing contracts. FT is interested in the manufacturer's demand rather than the final demand. Thus, once FT receives the manufacturer's order for components and requests for raw material inventory holding, it obtains information that will affect its inventory level decision in period 2. Recall that under an information sharing contract FT is held accountable for keeping a maximum inventory level *UB*. This inventory becomes available to the manufacturer in case of ST disruption. Nevertheless in case ST is UP in period 2, then FT is not required to maintain any inventory on site. Thus, we can derive the FT's optimal inventory level under an information sharing contract with the following profit structure using demand distribution $(Q_2)_n \sim N\left(\mu_n, (\sigma_{\mathrm{FT}})_n{}^2\right)$.

$(\pi_{\mathrm{FT}})_n$

$$= \begin{cases} p(d_1 + (I_{\mathrm{M}}^*)_n + (Q_2)_n) - p_{\mathrm{ST}}(d_1 + (I_{\mathrm{M}}^*)_n + (I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) \\ \qquad -p_{\mathrm{ST}} h_{\mathrm{FT}}((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) + \mathcal{C}_n \\ \qquad -p_{\mathrm{ST}}\big((Q_2)_n - ((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n)\big)^+ \\ \qquad +s_{\mathrm{FT}}\big(((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) - (Q_2)_n\big)^+, \text{ if the ST is not disrupted (Up)} \\ p(d_1 + (I_{\mathrm{M}}^*)_n + (Q_2)_n) - p_{\mathrm{ST}}(d_1 + (I_{\mathrm{M}}^*)_n + (I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) \\ \qquad -p_{\mathrm{ST}} h_{\mathrm{FT}}((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) + \mathcal{C}_n \\ \qquad -\big(p + (v - p)\big)\big((Q_2)_n - ((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n)\big)^+ \\ \qquad +p_{\mathrm{ST}}\big(((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) - (Q_2)_n\big)^+ \\ \qquad + (v - p)((Q_2)_n - (I_{\mathrm{MF}}^*)_n)^+, \qquad \text{if the ST is disrupted (Down)} \end{cases} \tag{9}$$

, where p_{ST} is raw material salvage value and $(I_{\mathrm{D}})_n$ is FT's deducted amount from the *UB* inventory level under ST's disruption, $(I_{\mathrm{MF}}^*)_n$. Note that $(I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n$ is FT's inventory level under mechanism type n, $(I_{\mathrm{FT}}^*)_n$, i.e., $(I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n = (I_{\mathrm{FT}}^*)_n$; ST might be disrupted with only probability $(1 - \beta)$, thus carrying all of manufacturer's request $(I_{\mathrm{MF}}^*)_n$ can be waste of cost from the FT's perspective In addition, note that by definition $\sigma_{\mathrm{FT}} = (\sigma_{\mathrm{FT}})_1 > (\sigma_{\mathrm{FT}})_2 = \sigma_{\mathrm{M}}$ and $\mu_1 = \mu_2 = \mu$. However, when the FT gathers the manufacturer's inventory level information, it can further revise its demand distribution as $(Q_2)_3 \sim N^C\big(\mu^C, {(\sigma_{\mathrm{FT}})_3}^2\big)$, where $\mu^C = \mu - (I_{\mathrm{M}}^*)_3$, $(\sigma_{\mathrm{FT}})_3 = \sigma_{\mathrm{M}}$ and $F_3(t)$ is corresponding c.d.f. Where N^C denotes a normal distribution with mean μ^C and standard deviation $(\sigma_{\mathrm{FT}})_3$ truncated at zero (i.e., $G_3(z) = G(z)$, if $z > \frac{-\left(\mu - (I_{\mathrm{M}}^*)_3\right)}{\sigma_{\mathrm{M}}}$, otherwise $G_3(z) = 0$). Thus, $\mu_3 = \mu^C - \int_0^{(I_{\mathrm{M}}^*)_3} (t - (I_{\mathrm{M}}^*)_3) dF(t) = \mu^C - \int_{-(I_{\mathrm{M}}^*)_3}^{0} t dF_C(t)$, where $F_C(t)$ is a normal c.d.f. with mean μ^C and standard deviation σ_{M}. Therefore, under information sharing, we assume that $F_3(t)$ is $F_C(t)$ censored at zero. The corresponding expected profit for FT is:

$$
\begin{aligned}
\mathrm{E}[(\pi_{\mathrm{FT}})_n] = {} & p(d_1 + (I_{\mathrm{M}}^*)_n + \mu_n) - p_{\mathrm{ST}}(d_1 + (I_{\mathrm{M}}^*)_n + (I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) \\
& - p_{\mathrm{ST}} h_{\mathrm{FT}}((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n) \\
& - (\beta s_{\mathrm{FT}} + (1-\beta) p_{\mathrm{ST}})\big(\mu_n - ((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n)\big) + \mathcal{C}_n \\
& - \big(\beta(p_{\mathrm{ST}} - s_{\mathrm{FT}}) \\
& + (1-\beta)(v - p_{\mathrm{ST}})\big) \int_{(I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n}^{\infty} \big(t - ((I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}})_n)\big)\, dF_n(t) \\
& + (1-\beta)(v-p) \int_{(I_{\mathrm{MF}}^*)_n}^{\infty} (t - (I_{\mathrm{MF}}^*)_n) dF_n(t)
\end{aligned} \tag{10}
$$

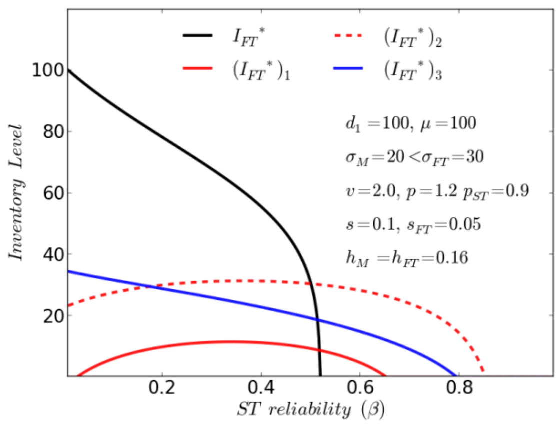


Figure E2-4: FT inventory level vs. ST reliability at $\boldsymbol{\alpha} = 0.7$

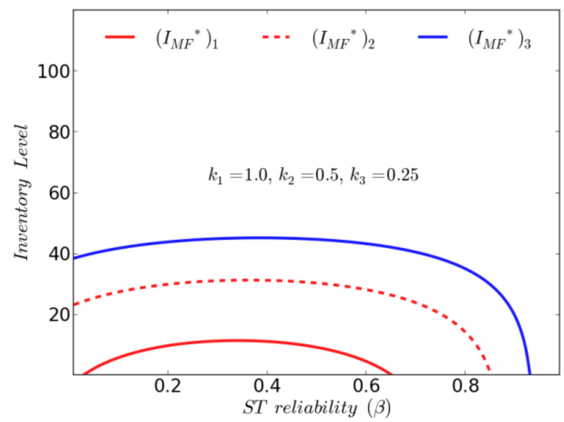


Figure E2-5: Manufacturer's requested FT inventory at $\boldsymbol{\alpha} = 0.7$

Proposition 6. When FT is paid for upstream information sharing by the manufacturer, its optimal preorder quantity $(I_{\mathrm{FT}}^*)_n$ in period 1 under information sharing contract n is given by:

$$
(I_{\mathrm{FT}}^*)_n = \max(0, (I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}}^*)_n)
$$

, where

$$
(I_{\mathrm{D}}^*)_n = \max\left(0, (I_{\mathrm{MF}}^*)_n - \left((\sigma_{\mathrm{FT}})_n G_n^{-1}\left(1 - \frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}} - \beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}} - s_{\mathrm{FT}}) + (1-\beta)(v - p_{\mathrm{ST}})}\right) + \mu_n\right)^+\right) \tag{11}
$$

Proof for Proposition 6 is included in Appendix F.

Proposition 7. For a given set of parameters, FT's optimal inventory levels, I_{FT}^{*} and $(I_{\mathrm{FT}}^{*})_n$, increase as ST disruption likelihood $1-\beta$ increases, if $(I_{\mathrm{D}}^{*})_n > 0$. Otherwise, the changes in optimal inventory levels depend on the values of $(I_{\mathrm{MF}}^{*})_n$.

Proof for Proposition 7 is included in Appendix G.

As we can see in Figure E2-4, under information sharing contract, FT can dramatically reduce its inventory level. It is interesting to note that even though FT does not directly receive final demand information from the manufacturer, the manufacturer's request $(I_{\mathrm{MF}}^{*})_n$ indirectly provides final demand information. However, this indirectly gathered demand information is incomplete. Thus, FT will try to stock an amount of inventory that is very close or equal to the manufacturer's requested amount. However, under the *FIS* information sharing mechanism, the demand information becomes complete so that FT can maintain lower inventory levels than those requested by the manufacturer.

4. Numerical Experiments

In this section, we numerically investigate the impact of using the different information sharing contracts on the manufacturer's and FT's profits.

4.1. Value of Information from Manufacturer's Perspective

We showed previously that the manufacturer's expected profits as well as optimal decisions such as how much inventory to stock at the manufacturer and FT tend to show similar behavior under the different contracts considered. Thus, we mainly focus our analysis on the *IB* information sharing contract.

Figure E2-6 shows that the effect of the information sharing contract (on the manufacturer's profit) is contingent not only on FT's reliability (α) but also on ST's reliability (β).

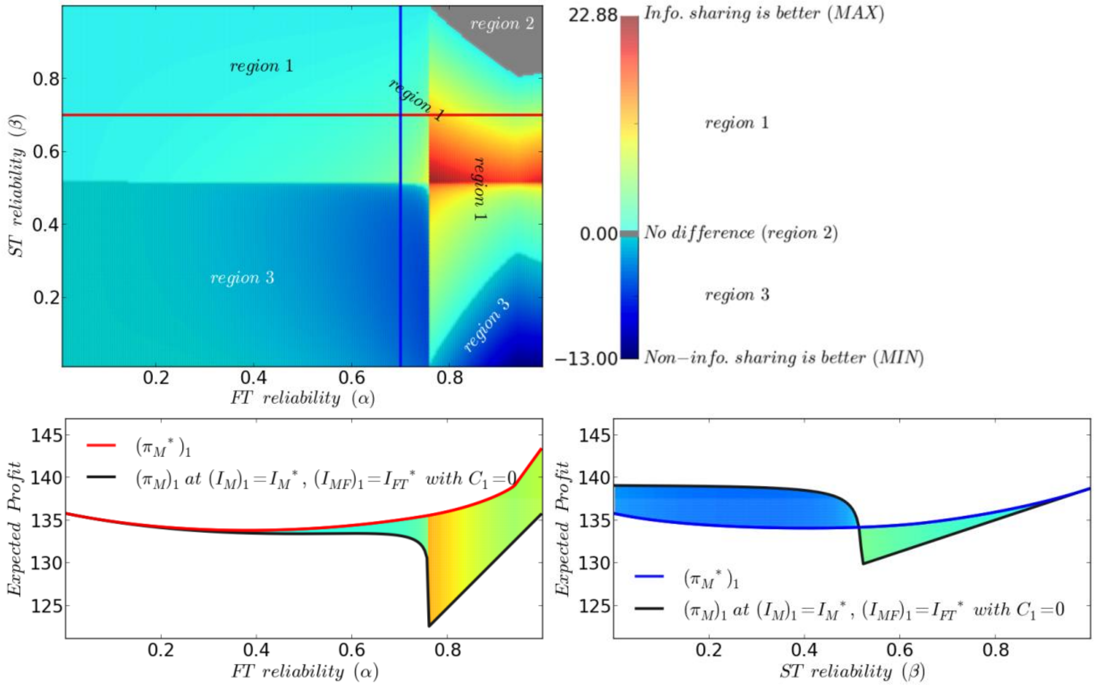


Figure E2-6: Manufacturer's profit comparison 1, i.e., Non-information sharing vs. Information sharing with *IB* with the same parameters used in section 3, i.e., $\boldsymbol{v} = 2.0$, $\boldsymbol{p} = 1.2$, $\boldsymbol{p}_{\mathrm{ST}} = 0.9$, $\boldsymbol{s} = 0.1$, and $\boldsymbol{h}_{\mathrm{M}} = \boldsymbol{h}_{\mathrm{FT}} = 0.16$; The two plots on the bottom are the sectional views of the plot on the top at $\boldsymbol{\alpha} = 0.7$ and $\boldsymbol{\beta} = 0.7$.

When both FT and ST reliabilities are very high (region 2 of the top plot), $(I_{\mathrm{M}}^*)_1 = I_{\mathrm{M}}^* = 0$ and $(I_{\mathrm{MF}}^*)_1 = 0$ (by proposition 3), the manufacturer will not invest in holding inventory at FT's site. This implies that $\mathrm{E}[\pi_{\mathrm{M}}] = \mathrm{E}[(\pi_{\mathrm{M}})_1]$. When FT reliability is very high but ST reliability is very low (lower right region 3 of the top plot), using an information sharing contract adversely affects manufacturer's profit. FT will maintain very high inventory levels, when the ST is very unreliable even under non-information sharing. Thus, paying for holding inventory at the FT's site is not an effective strategy from the manufacturer's perspective. Similar results can be observed at the right side of the lower left region 3 of the top plot. However, in this region, the loss decreases as FT's reliability decreases, as shown in Figure E2-2, by proposition 3, $(I_{\mathrm{M}}^*)_1 \to I_{\mathrm{M}}^*$ and $(I_{\mathrm{MF}}^*)_1 \to 0$ as $\alpha \to 0$. The area denoted as region 1 represents positive profits for the manufacturer.

Under non-information sharing, the manufacturer's decision for its own inventory level is not affected by ST's reliability, but it is affected under information sharing contract (refer to Figure E2-3). Therefore, the discrepancy in manufacturer's own inventory levels (i.e., between $(I_{\mathrm{M}}^{*})_1$ and I_{M}^{*}) and positive $(I_{\mathrm{MF}}^{*})_1$ make the discrepancy between $\mathrm{E}[(\pi_{\mathrm{M}})_1]$ and $\mathrm{E}[\pi_{\mathrm{M}}]$. It is positive when the FT reliability is relatively high and ST reliability is relatively low (lower right side of Figure E2-7.1 and E2-7.2). However, $\alpha \to 0$ or $\beta \to 1$ leads $(I_{\mathrm{M}}^{*})_n \to I_{\mathrm{M}}^{*}$ and $(I_{\mathrm{MF}}^{*})_n \to 0$. Thus, the positive effect will diminish as FT's reliability decreases or ST's reliability increases. Similar results are derived from the *SIS* and *FIS* mechanism.

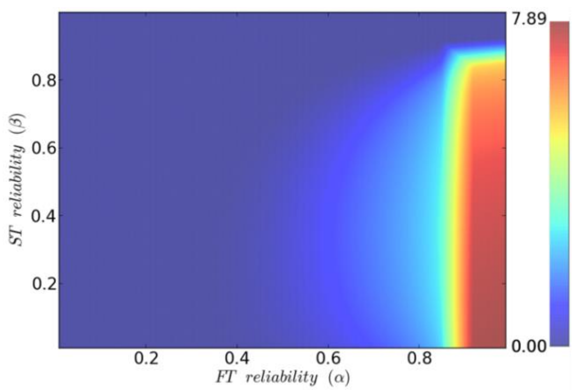


Figure E2-7.1: Manufacturer's profit comparison 2, i.e., *IB* vs. *SIS* (Manufacturer's profit in *IB* − manufacturer's profit in *SIS*)

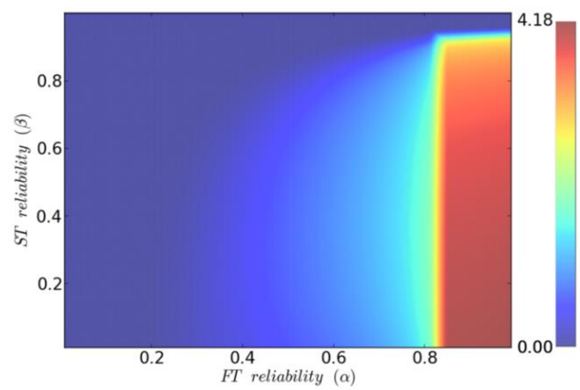
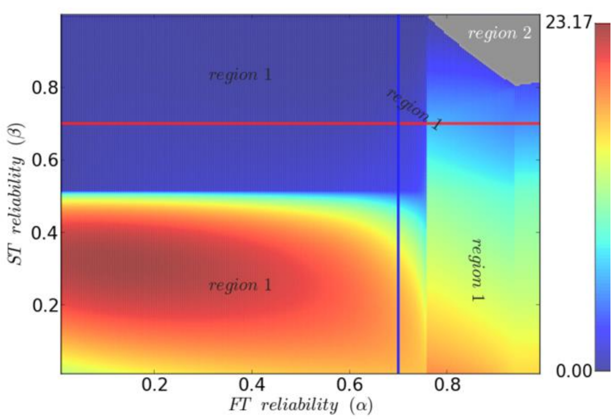


Figure E2-7.2: Manufacturer's profit comparison 3, i.e., *SIS* vs. *FIS* (Manufacturer's profit in *SIS* − manufacturer's profit in *FIS*)

By definition, information sharing costs are different under the three mechanisms considered, i.e., $k_1 > k_2 > k_3$. Thus, greater benefits can be obtained for information sharing contracts type 2 and 3. From Figure E2-7.1 and E2-7.2, we can conclude that the *FIS* information sharing contract is the preferred information sharing mechanism by the manufacturer, since anywhere in Figures E2-7.1 and E2-7.2 does not have negative value.

4.2. Value of Information from FT's Perspective

We assume that FT's demand forecast is less accurate than the manufacturer's under non-information sharing and that FT's revised forecast is incomplete under *IB* and *SIS* sharing contracts. The basic assumption is that the most accurate demand forecasting in period 2 is the manufacturer's, i.e., $D_2 \sim N(\mu, \sigma_{\mathrm{M}}^2)$. Thus, the manufacturer's order size in period 2 is $D_2 \sim N^C(\mu - I_{\mathrm{M}}, \sigma_{\mathrm{M}}^2)$. However, FT can know I_{M} only under *FIS*. Therefore, the inventory level decisions of FT under non-information sharing and *IB* and *SIS* contracts are the optimal solution based on incomplete demand information. This implies that the expected profit with these solutions might not be the best profit. This further implies that the solution under *FIS* is the optimal with complete demand information (Note that it does not mean *FIS* is the best mechanism for the FT in terms of profits.)



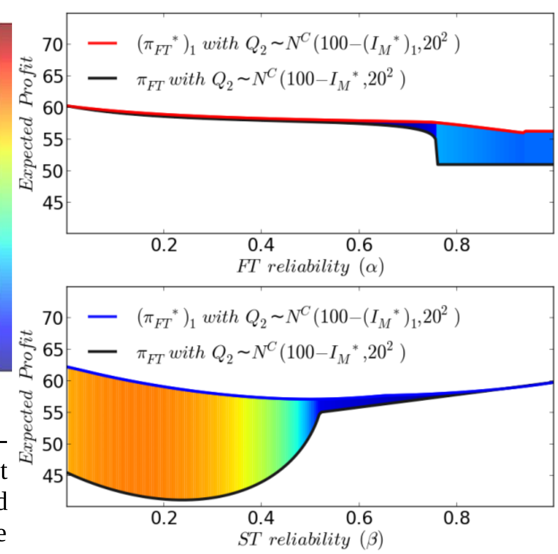


Figure E2-8: FT's profit comparison 1, i.e., Non-Information sharing vs. Information sharing with *IB* at $\boldsymbol{v} = 2.0$, $\boldsymbol{p} = 1.2$, $\boldsymbol{p}_{\mathrm{ST}} = 0.9$, $\boldsymbol{s} = 0.1$, $\boldsymbol{s}_{\mathrm{FT}} = 0.05$ and $\boldsymbol{h}_{\mathrm{M}} = \boldsymbol{h}_{\mathrm{FT}} = 0.16$; The two plots on the right are the sectional views of the plot on the left at $\boldsymbol{\alpha} = 0.7$ and $\boldsymbol{\beta} = 0.7$.

From the left plot of Figure E2-8, it is evident that the *IB* contract does not adversely impact FT's profit for a given set of parameters. Similar to the manufacturer's case, when ST's reliability and the manufacturer's evaluation of FT's reliability are very high, FT's profit will not change compared to the non-information sharing case (region 2). When the manufacturer's evaluation of FT's reliability is not very high but ST's reliability is relatively high, i.e., upper-left part of region 1, the manufacturer will require very low inventory levels. In this case, FT will carry very low levels of inventory or no inventory at all as indicated in Figure E2-4 under both information sharing and non-information sharing contracts. Consequently, the difference between information sharing and non-information sharing is very small. This implies that the improvement in FT's profit is not significant. The lower left part of region 1 shows a very high positive effect on FT's profit. In this region, because of low ST reliability, FT will be more likely to carry very high levels of inventory (Figure E2-4) under non-information sharing. However, in this region, the information sharing contract will provide a chance to revise the demand forecast, since the manufacturer will increase its own inventory level rather than asking the FT to carry more inventories because of low reliability of FT. This revised demand enables FT to reduce unnecessary inventory dramatically, reducing inventory holding costs. When the manufacturer's evaluation of FT reliability is high enough but ST reliability is not very high (right side of region 1), FT can receive high reward for inventory holding from the manufacturer (Figure E2-2 and E2-3). This increases FT's profit. In this case, FT can increase profits by receiving financial support from the manufacturer rather than decreasing inventory levels.

Table E2-2: FT's profit of Information sharing mechanisms – FT's profit of Non-information sharing

Mechanism Type	**Reward**	**Max / Min**	**Region 1 Positive Profit Area**	**Region 2 Indifference Area**	**Region 3 Negative Profit Area**
IB	$k_1 = 1.00$	23.17 / 0.00	97.31%	2.69%	--
SIS	$k_2 = 0.50$	23.17 / - 4.41	79.54%	2.07%	18.39%
FIS	$k_3 = 0.25$	23.17 / - 6.63	66.53%	1.45%	30.02%

For a specific set of parameters the manufacturer's as well as FT's profits tend to change in similar ways under the three information sharing mechanisms considered, but the level of impact on profits is different. Table E2-2 shows FT's profit obtained with the different information sharing mechanisms relative to the non-information sharing case. By setting k_1, k_2, and k_3 to 1.0, 0.5, and 0.25, respectively. *IB* generates the broadest positive profit area, i.e., the area of $\mathrm{E}[(\pi_{\mathrm{FT}})_1] - \mathrm{E}[\pi_{\mathrm{FT}}] > 0$, with the narrowest range of profit values (from 23.17 to 0.00). On the other hand, *FIS* generates the narrowest positive profit area with the widest profit values (from 23.17 to - 6.63).

Table E2-3: Performance of information sharing mechanisms under $\boldsymbol{k_1 = k_2 = k_3}$

Mechanism Type	**Reward**	**Max / Min**	**Region 1 Positive Profit Area**	**Region 2 Indifference Area**	**Region 3 Negative Profit Area**
SIS	$k_2 = 1.00$	23.17 / 0.00	97.31%	2.69%	--
FIS	$k_3 = 1.00$	23.17 / 0.00	97.31%	2.69%	--
IB	$k_1 = 0.50$	23.17 / - 4.41	79.54%	2.07%	18.39%
FIS	$k_2 = 0.50$	23.17 / - 2.78	81.40%	2.07%	16.53%
IB	$k_1 = 0.25$	23.17 / -11.98	62.60%	1.45%	35.95%
SIS	$k_2 = 0.25$	23.17 / -11.98	63.43%	1.45%	35.12%

By setting $k_2 = k_3 = k_1 = 1.00$, the results in Table E2-3 show that additional information under *SIS* and *FIS* does not improve the FT's profit compared to the profit under *IB* (*SIS* and *FIS* become identical to *IB*). Under this setting, by proposition 2, $(I^*_{\mathrm{MF}})_1 = (I^*_{\mathrm{MF}})_2 = (I^*_{\mathrm{MF}})_3$, and $(I^*_{\mathrm{D}})_1 = (I^*_{\mathrm{D}})_2 = (I^*_{\mathrm{D}})_3 = 0$ (by proposition 6) for a given set of parameters. Thus, all the mechanisms become identical. Moreover, by setting $k_2 = k_3 = k_1 = 0.25$ and $k_2 = k_3 = k_1 = 0.50$, *FIS* becomes the best mechanism but the difference in the profit improvement is not significant. The results in Tables E2-2 and E2-3 imply that FT prefers *IB* to the other mechanisms, since *IB* can indirectly provide downstream information with high rewards and the added value of complete information does not play a significant role in profit improvement from FT's perspective.

5. Concluding Remarks

A number of articles in the literature recognize the importance of information sharing. However, estimating the value of information so that appropriate incentives for information sharing are implemented can be challenging. In this paper, we first characterize the manufacturer's and FT's sourcing behaviors under non-information sharing and then compare it to three different information sharing contracts. We show that the manufacturer becomes more conservative, while the FT becomes more proactive under an information sharing contract. With these findings, we analyze the effectiveness of three different information sharing mechanisms.

The results show that the benefits of information sharing are contingent on the level of FT and ST reliabilities from the manufacturer's and FT's perspective. However, we show that the manufacturer and FT tend to prefer different types of information sharing contracts, since information does not provide equal benefits to both parties. The manufacturer prefers to reduce information sharing costs by providing downstream information to the FT, i.e., *FIS* information sharing contract is preferred. On the other hand, the FT prefers the *IB* information sharing contract because it can indirectly provide downstream information as well as high rewards. Therefore, appropriate selection of information sharing mechanisms is a key factor for each player in the supply chain.

It is important to point out that in our analysis the ST is not the main decision maker. Addition of the ST as a decision maker could be an interesting extension of this paper in order to examine the different dynamics among all parties in the supply chain.

In this paper, we did not investigate the supply chain coordination issue because we assume that each entity (manufacturer and FT) believes that only its upstream entity(s) will be likely to be disrupted but the downstream entity(s) will not be disrupted in the future. However, it would be interesting to examine the value of information sharing from the supply chain coordination perspective by applying the assumption that all the upstream and downstream members can be disrupted. For this future direction, simulation can be an appropriate approach by applying random disruption on every entity in the supply chain.

APPENDICES

Appendix A: Proof of Proposition 1

Proof 1. Given variable t with mean μ_t, standard deviation σ_t, and cumulative distribution $F(t)$, we define the standardized variable z to be $z = \frac{t-\mu_t}{\sigma_t}$. z has cumulative distribution $G(z)$ with mean 0 and standard deviation 1. Given a value R of t, we define $(R)_z = \frac{R-\mu_t}{\sigma_t}$. The standardized loss function is defined as $L(t,(R)_z) = \int_{(R)_z}^{\infty}\big(1-G(z)\big)\,dz$. Equation (2) can be modified as follows by applying $\mu_t = \mu$ and $\sigma_t = \sigma_{\mathrm{M}}$.

$$\begin{aligned}
\mathrm{E}[\pi_{\mathrm{M}}] = (v-p)d_1 - \big(v-(\alpha s+(1-\alpha)p)\big)\mu \\
-\big((1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)\big)I_{\mathrm{M}} \\
-\big(\alpha(p-s)+(1-\alpha)(v-p)\big)\int_{I_{\mathrm{M}}}^{\infty}(t-I_{\mathrm{M}})\,dF(t) \qquad (A1)
\end{aligned}$$

$$\begin{aligned}
= (v-p)d_1 - \big(v-(\alpha s+(1-\alpha)p)\big)\mu - \big((1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)\big)I_{\mathrm{M}} \\
- \big(\alpha(p-s)+(1-\alpha)(v-p)\big)\sigma_{\mathrm{M}}\int_{(I_{\mathrm{M}})_z}^{\infty}\big(1-G(z)\big)\,dz
\end{aligned}$$

By definition of the standardized loss function, $L(t,(R)_z)$, $(A1)$ can be expressed as

$$\begin{aligned}
\mathrm{E}[\pi_{\mathrm{M}}] = (v-p)d_1 - \big(v-(\alpha s+(1-\alpha)p)\big)\mu - \big((1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)\big)I_{\mathrm{M}} \\
- \big(\alpha(p-s)+(1-\alpha)(v-p)\big)\sigma_{\mathrm{M}}L(t,(I_{\mathrm{M}})_z)
\end{aligned}$$

We can observe that $\frac{\partial L(t,(I_{\mathrm{M}})_z)}{\partial I_{\mathrm{M}}} = -\frac{1}{\sigma_{\mathrm{M}}}\left(1-G\left(\frac{I_{\mathrm{M}}-\mu}{\sigma_{\mathrm{M}}}\right)\right)$ and $\frac{\partial^2 L(t,(I_{\mathrm{M}})_z)}{\partial^2 I_{\mathrm{M}}} = \frac{1}{\sigma_{\mathrm{M}}{}^2}g\left(\frac{I_{\mathrm{M}}-\mu}{\sigma_{\mathrm{M}}}\right) \geq 0$, which implies that the standardized loss function is convex. Thus, we further can observe that $\frac{\partial \mathrm{E}[\pi_{\mathrm{M}}]}{\partial I_{\mathrm{M}}} = -\big((1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)\big) - \sigma_{\mathrm{M}}\big(\alpha(p-s)+(1-\alpha)(v-p)\big)\frac{\partial L(t,(I_{\mathrm{M}})_z)}{\partial I_{\mathrm{M}}}$ and $\frac{\partial^2 \mathrm{E}[\pi_{\mathrm{M}}]}{\partial^2 I_{\mathrm{M}}} = -\sigma_{\mathrm{M}}\big(\alpha(p-s)+(1-\alpha)(v-p)\big)\frac{\partial^2 L(t,(I_{\mathrm{M}})_z)}{\partial^2 I_{\mathrm{M}}}$ implying that $\mathrm{E}[\pi_{\mathrm{M}}]$ is concave since $\big(\alpha(p-s)+(1-\alpha)(v-p)\big) > 0$. Therefore, I_{M}^* is obtained by setting $\frac{\partial \mathrm{E}[\pi_{\mathrm{M}}]}{\partial I_{\mathrm{M}}} = 0$, which gives $\big((1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)\big) + \big(\alpha(p-s)+$

$(1-\alpha)(v-p))\left(1-G\left(\frac{I_{\mathrm{M}}-\mu}{\sigma_{\mathrm{M}}}\right)\right)=0$. By solving for I_{M}, The optimal inventory level is given by $I_{\mathrm{M}}^{*}=\max\left(0,\sigma_{\mathrm{M}}G^{-1}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)+\mu\right)$. However, since $I_{\mathrm{M}}\geq 0$, we obtain the optimal I_{M}^{*} as following.

$$I_{\mathrm{M}}^{*}=\max\left(0,\sigma_{\mathrm{M}}G^{-1}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)+\mu\right)$$

If $I_{\mathrm{M}}^{*}>0$, i.e., $\sigma_{\mathrm{M}}G^{-1}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)>-\mu$, this implies that $1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}>G\left(-\frac{\mu}{\sigma_{\mathrm{M}}}\right)=F(0)=0$, by assumption of non-negative demand. By simple algebra, this can be rearranged as $\frac{v}{p}>\frac{1-\alpha+h_{\mathrm{M}}}{1-\alpha}$, which implies that only when the ratio $\frac{v}{p}$ exceeds $\frac{1-\alpha+h_{\mathrm{M}}}{1-\alpha}$, the manufacturer will carry positive inventory. The properties of I_{M}^{*} are as follows. When $I_{\mathrm{M}}^{*}>0$, I_{M}^{*} is increasing (decreasing) in v (p). Since $G^{-1}(\cdot)$ is monotone increasing function, but $\frac{\partial}{\partial v}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)=\frac{(1-\alpha)\left((h_{\mathrm{M}}+\alpha)p-\alpha s\right)}{\left((2\alpha-1)p+(1-\alpha)v-\alpha s\right)^{2}}>0$ and $\frac{\partial}{\partial p}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)=\frac{(1-\alpha+h_{\mathrm{M}})\alpha s-(\alpha+h_{\mathrm{M}})(1-\alpha)v}{\left((2\alpha-1)p+(1-\alpha)v-\alpha s\right)^{2}}<0$ (because $\frac{v}{p}>\frac{1-\alpha+h_{\mathrm{M}}}{1-\alpha}$ when $I_{\mathrm{M}}^{*}>0$, but $\frac{v}{p}<\frac{(\alpha+h_{\mathrm{M}})v}{\alpha s}$ so that numerator is negative), which imply that I_{M}^{*} increases (decreases) in v (p) (similarly, we can prove that I_{M}^{*} increases in s, when $I_{\mathrm{M}}^{*}>0$). Moreover, $\frac{\partial}{\partial \alpha}\left(1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right)=\frac{(1-\alpha+h_{\mathrm{M}})\alpha s-(\alpha+h_{\mathrm{M}})(1-\alpha)v}{\left((2\alpha-1)p+(1-\alpha)v-\alpha s\right)^{2}}<0$, since $\frac{v}{p}>\frac{1-\alpha+h_{\mathrm{M}}}{1-\alpha}$ when $I_{\mathrm{M}}^{*}>0$ (thus numerator is negative). Therefore, as α increases, I_{M}^{*} decreases. By definition of the normal inverse c.d.f., $F_{S}^{-1}(0.5)=0$, implying that if $1-\frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}<0.5\Leftrightarrow\frac{v+s\alpha(1-\alpha)^{-1}}{p}<\frac{1+2h_{\mathrm{M}}}{1-\alpha}$, I_{M}^{*} is decreasing in σ_{M}, otherwise I_{M}^{*} is increasing in σ_{M}. ■

Appendix B: Proof of Proposition 2

Proof 2. Similar to the base case, we can derive Equation (4) as follows.

$$
\begin{aligned}
\mathrm{E}[(\pi_{\mathrm{M}})_n] = {} & v(d_1+\mu) - p(d_1+(I_{\mathrm{M}})_n) - ph_{\mathrm{M}}(I_{\mathrm{M}})_n \\
& - (\alpha(1-\beta)p + (1-\alpha)p + \alpha\beta s)(\mu - (I_{\mathrm{M}})_n) - \mathcal{C}_n \\
& - (\alpha\beta p + (1-\alpha)v - (1-\alpha)p - \alpha\beta s)\int_{(I_{\mathrm{M}})_n}^{\infty} (t-(I_{\mathrm{M}})_n)\, dF(t) \\
& - \alpha(1-\beta)(v-p)\int_{(I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n}^{\infty} \big(t-((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)\big)\, dF(t)
\end{aligned}
$$

Observe that

$$\int_{(I_{\mathrm{M}})_n}^{\infty} (t-(I_{\mathrm{M}})_n)\, dF(t) = \sigma_{\mathrm{M}} L(t,((I_{\mathrm{M}})_n)_z) \text{ and}$$

$$\int_{(I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n}^{\infty} \big(t-((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)\big)\, dF(t) = \sigma_{\mathrm{M}} L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z)$$

Thus, we have

$$
\begin{aligned}
\mathrm{E}[(\pi_{\mathrm{M}})_n] = {} & v(d_1+\mu) - p(d_1+(I_{\mathrm{M}})_n) - ph_{\mathrm{M}}(I_{\mathrm{M}})_n \\
& - (\alpha(1-\beta)p + (1-\alpha)p + \alpha\beta s)(\mu - (I_{\mathrm{M}})_n) - \mathcal{C}_n \\
& - (\alpha\beta p + (1-\alpha)v - (1-\alpha)p - \alpha\beta s)\sigma_{\mathrm{M}} L(t,((I_{\mathrm{M}})_n)_z) \\
& - \alpha(1-\beta)(v-p)\sigma_{\mathrm{M}} L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z).
\end{aligned}
$$

We further observe that

$$\frac{\partial L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z)}{\partial (I_{\mathrm{M}})_n} = \frac{\partial L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z)}{\partial (I_{\mathrm{MF}})_n} = -\frac{1}{\sigma_{\mathrm{M}}}\left(1 - G\left(\frac{(I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n-\mu}{\sigma_{\mathrm{M}}}\right)\right)$$

$$\frac{\partial L(t,((I_{\mathrm{M}})_n)_z)}{\partial (I_{\mathrm{M}})_n} = -\frac{1}{\sigma_{\mathrm{M}}}\left(1 - G\left(\frac{(I_{\mathrm{M}})_n-\mu}{\sigma_{\mathrm{M}}}\right)\right)$$

By applying $\mathcal{C}_n = p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})(I_{\mathrm{MF}})_n$, we can derive the following results.

$$\frac{\partial \mathrm{E}[(\pi_{\mathrm{M}})_n]}{\partial (I_{\mathrm{MF}})_n} = -p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}}) - \alpha(1-\beta)(v-p)\sigma_{\mathrm{M}} \frac{\partial L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z)}{\partial (I_{\mathrm{MF}})_n} \tag{$B1$}$$

$$\begin{aligned} \frac{\partial \mathrm{E}[(\pi_{\mathrm{M}})_n]}{\partial (I_{\mathrm{M}})_n} = {} & -h_{\mathrm{M}}p - \alpha\beta(p-s) \\ & - \big(\alpha\beta(p-s) + (1-\alpha)(v-p)\big)\sigma_{\mathrm{M}} \frac{\partial L(t,((I_{\mathrm{M}})_n)_z)}{\partial (I_{\mathrm{M}})_n} \\ & - \alpha(1-\beta)(v-p)\sigma_{\mathrm{M}} \frac{\partial L(t,((I_{\mathrm{M}})_n+(I_{\mathrm{MF}})_n)_z)}{\partial (I_{\mathrm{M}})_n} \end{aligned} \tag{$B2$}$$

Given that $\frac{\partial \mathrm{E}\left[(\pi_{\mathrm{M}})_n\right]}{\partial (I_{\mathrm{MF}})_n} = 0$ at optimality, by substituting $(B1)$, we obtain $(B2)$ as follows.

$$\begin{aligned} \frac{\partial \mathrm{E}[(\pi_{\mathrm{M}})_n]}{\partial (I_{\mathrm{M}})_n} = {} & -h_{\mathrm{M}}p - \alpha\beta(p-s) - \big(\alpha\beta(p-s) + (1-\alpha)(v-p)\big)\sigma_{\mathrm{M}} \frac{\partial L(t,((I_{\mathrm{M}})_n)_z)}{\partial (I_{\mathrm{M}})_n} \\ & + p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}}) \end{aligned}$$

By setting $\frac{\partial \mathrm{E}\left[(\pi_{\mathrm{M}})_n\right]}{\partial (I_{\mathrm{M}})_n} = 0$ and $\frac{\partial \mathrm{E}\left[(\pi_{\mathrm{M}})_n\right]}{\partial (I_{\mathrm{MF}})_n} = 0$, we obtain the optimal manufacturer's and FT's inventory levels.

$$(I_{\mathrm{M}}^*)_n = \max\left(0, \sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{(h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s - p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)}\right) + \mu\right) \text{ and} \tag{$B3$}$$

$$(I_{\mathrm{MF}}^*)_n = \sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}\right) + \mu - (I_{\mathrm{M}}^*)_n \text{ respectively.} \tag{$B4$}$$

CASE 1) We know that I_{MF} should be non-negative as well. This implies that this optimal relationship holds only when $\sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}\right) + \mu - (I_{\mathrm{M}}^*)_n > 0$.

i) When $(I_{\mathrm{M}}^*)_n > 0$, the following should hold.

$$\begin{aligned} & G^{-1}\left(1 - \frac{p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}\right) - G^{-1}\left(1 - \frac{(h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s - p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)}\right) > 0 \Leftrightarrow \frac{p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)} \\ & < \frac{(h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s - p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)} \Leftrightarrow p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}}) \\ & < \delta\big((h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s\big)(\gamma+\delta)^{-1} \end{aligned}$$

ii) When $(I_{\mathrm{M}}^*)_n = 0$, the following should hold.

$$G^{-1}\left(1 - \frac{p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}\right) > -\frac{\mu}{\sigma_{\mathrm{M}}} \Leftrightarrow p_2(k_n \cdot h_{\mathrm{F}}) < \delta$$

, where $\delta = \alpha(1-\beta)(v-p)$ (>0) and $\gamma = \alpha\beta(p-s) + (1-\alpha)(v-p)$ (>0).

Thus, in this case, i.e., $I_{\mathrm{MF}} \geq 0$, the optimal solution is given by $(B3)$ and $(B4)$.

CASE 2) When this condition does not hold, i.e., $(I_{\mathrm{MF}})_n < 0$, by fixing $(I_{\mathrm{MF}})_n^* = 0$ and plugging this to equation (5), we can find optimal the solution of I_{M} as in Proposition 1. The optimal solution for this case is given by

$$(I_{\mathrm{M}}^*)_n = \max\left(0, \sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{(h_{\mathrm{M}}+\alpha\beta)p - \alpha\beta s}{\alpha\beta(p-s)+(1-\alpha\beta)(v-p)}\right) + \mu\right) \text{ and } (I_{\mathrm{MF}}^*)_n = 0 \text{ respectively.}$$

■

Appendix C: Proof of Proposition 3

Proof 3. $G^{-1}(\cdot)$ and $G(\cdot)$ are monotone increasing with support from 0 to 1. First, we consider the case of $(I_{\mathrm{MF}}^{*})_n > 0$. $I_{\mathrm{M}}^{*} > 0$ means $\frac{(h_{\mathrm{M}}+\alpha)p-\alpha s}{\alpha(p-s)+(1-\alpha)(v-p)} < 1$, since $\sigma_{\mathrm{M}} G^{-1}\left(1 - \frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)}\right) + \mu > 0 \Leftrightarrow 1 - \frac{(1+h_{\mathrm{M}})p-(\alpha s+(1-\alpha)p)}{\alpha(p-s)+(1-\alpha)(v-p)} > G\left(-\frac{\mu}{\sigma_{\mathrm{M}}}\right) \geq 0 \Longrightarrow 1 \geq \frac{(h_{\mathrm{M}}+\alpha)p-\alpha s}{\alpha(p-s)+(1-\alpha)(v-p)}$ (Let $(h_{\mathrm{M}}+\alpha)p - \alpha s = \mathcal{A}$ and $\alpha(p-s)+(1-\alpha)(v-p) = \mathcal{B}$). In this case, we claim that $(I_{\mathrm{M}}^{*})_n > I_{\mathrm{M}}^{*} \Leftrightarrow G^{-1}\left(1 - \frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s-p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)}\right) > G^{-1}\left(1 - \frac{(h_{\mathrm{M}}+\alpha)p-\alpha s}{\alpha(p-s)+(1-\alpha)(v-p)}\right)$. But, $0 \leq \frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s-p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)} = \frac{\mathcal{A}-\alpha(1-\beta)(p-s)-p_{\mathrm{ST}}(k_n \cdot h_{\mathrm{FT}})}{\mathcal{B}-\alpha(1-\beta)(p-s)} < \frac{\mathcal{A}}{\mathcal{B}} \leq 1$, which implies that $(I_{\mathrm{M}}^{*})_n > I_{\mathrm{M}}^{*}$. Second, we consider the case of $(I_{\mathrm{MF}}^{*})_n = 0$. In this case, when $I_{\mathrm{M}}^{*} > 0$, $(I_{\mathrm{M}}^{*})_n > I_{\mathrm{M}}^{*}$ means $\frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s}{\alpha\beta(p-s)+(1-\alpha\beta)(v-p)} \leq \frac{\mathcal{A}}{\mathcal{B}}$. But, $0 \leq \frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s}{\alpha\beta(p-s)+(1-\alpha\beta)(v-p)} = \frac{\mathcal{A}-\alpha(1-\beta)(p-s)}{\mathcal{B}-\alpha(1-\beta)(p-s)+\alpha(1-\beta)(v-p)} \leq \frac{\mathcal{A}}{\mathcal{B}} \leq 1$. Therefore, $(I_{\mathrm{M}}^{*})_n$ cannot be less than I_{M}^{*} in either case. (We can ignore the case of $I_{\mathrm{M}}^{*} = 0$, since $(I_{\mathrm{M}}^{*})_n$ cannot be negative by definition). ■

Appendix D: Proof of Proposition 4

Proof 4. Let $\mathcal{G}_{\mathrm{M}}^{+}=1-\frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})}{\alpha\beta(p-s)+(1-\alpha)(v-p)}$, $\mathcal{G}_{\mathrm{M}}^{o}=1-\frac{(h_{\mathrm{M}}+\alpha\beta)p-\alpha\beta s}{\alpha\beta(p-s)+(1-\alpha\beta)(v-p)}$, and $\mathcal{H}_{\mathrm{M}}=1-\frac{p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})}{\alpha(1-\beta)(v-p)}$. When $(I_{\mathrm{MF}}^{*})_n>0$, if $\mathcal{G}_{\mathrm{M}}^{+}$ is decreasing as α increases, $(I_{\mathrm{M}}^{*})_n$ is decreasing as α increases, since $G^{-1}(\cdot)$ is monotone increasing function. But, $\frac{\partial\mathcal{G}_{\mathrm{M}}^{+}}{\partial\alpha}=\frac{\beta(p-s)\left(\left(ph_{\mathrm{M}}-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})\right)-(v-p)\right)-(v-p)\left(ph_{\mathrm{M}}-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})\right)}{\left(\alpha\beta(p-s)+(1-\alpha)(v-p)\right)^2}<0$, since $ph_{\mathrm{M}}-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})>0$ and $\left(ph_{\mathrm{M}}-p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})\right)-(v-p)<ph_{\mathrm{M}}-(v-p)<0$ (note that if $v-p<ph_{\mathrm{M}}$, the manufacturer will not carry any inventory). Similarly, when $(I_{\mathrm{MF}}^{*})_n=0$, this property still holds, since $\frac{\partial\mathcal{G}_{\mathrm{M}}^{o}}{\partial\alpha}\le 0$. We can further show that $(I_{\mathrm{M}}^{*})_n$ is always decreasing as β, since $\frac{\partial\mathcal{G}_{\mathrm{M}}^{+}}{\partial\beta},\frac{\partial\mathcal{G}_{\mathrm{M}}^{o}}{\partial\beta}<0$. On the other hand, $(I_{\mathrm{MF}}^{*})_n$ is increasing as α increases, since $\frac{\partial\mathcal{H}_{\mathrm{M}}}{\partial\alpha}=\frac{p_{\mathrm{ST}}(k_n\cdot h_{\mathrm{FT}})}{\alpha^2(1-\beta)(v-p)}>0$ (when $(I_{\mathrm{MF}}^{*})_n>0$). However, we cannot guarantee the property of $(I_{\mathrm{MF}}^{*})_n$ associated with β, since both $G^{-1}(\mathcal{H}_{\mathrm{M}})$ and $(I_{\mathrm{M}}^{*})_n$ are decreasing in β. This result further implies that the joint inventory, i.e., $(I_{\mathrm{M}}^{*})_n+(I_{\mathrm{MF}}^{*})_n$, is increasing (decreasing) as α (β) increases, since $(I_{\mathrm{M}}^{*})_n+(I_{\mathrm{MF}}^{*})_n=\sigma_{\mathrm{M}}G^{-1}(\mathcal{H}_{\mathrm{M}})+\mu$, when $(I_{\mathrm{MF}}^{*})_n>0$. But, when $(I_{\mathrm{MF}}^{*})_n=0$, $(I_{\mathrm{M}}^{*})_n+(I_{\mathrm{MF}}^{*})_n=(I_{\mathrm{M}}^{*})_n=\sigma_{\mathrm{M}}G^{-1}(\mathcal{G}_{\mathrm{M}}^{o})+\mu$. Thus, $(I_{\mathrm{M}}^{*})_n+(I_{\mathrm{MF}}^{*})_n$ is decreasing as α and/or β increases. Therefore, the joint inventory is increasing or decreasing as α increases but decreasing as β increases. ■

Appendix E: Proof of Proposition 5

Proof 5. Replication of Proof 1 (by replacing I_{M}, σ_{M}, h_{M}, p, s, and v with I_{FT}, σ_{FT}, h_{FT}, p_{ST}, and p, respectively) quite easily derives I_{FT}^{*}. ■

Appendix F: Proof of Proposition 6

Proof 6. $L_n(t,((I_{\mathrm{FT}})_n)_z) = \int_{((I_{\mathrm{FT}})_n)_z}^{\infty} \left(1 - G_n(z)\right) dz$, where $G_1$and G_2 are standard normal c.d.f. and G_3 is left truncated standard normal c.d.f. at $\frac{-\left(\mu-(I_{\mathrm{M}}^*)_3\right)}{\sigma_{\mathrm{M}}}$.

For $n = 1$ and 2 , $L_n(t,(R)_z) = g((R)_z) - \frac{R-(\mu_n)}{(\sigma_{\mathrm{FT}})_n}[1 - G((R)_z)]$. And, for $n = 3$, $L_n(t,(R)_z) = \frac{\sigma_{\mathrm{M}}}{(\sigma_{\mathrm{FT}})_3}[g((R)_z)] - \frac{R-(\mu-(I_{\mathrm{M}}^*)_3)}{(\sigma_{\mathrm{FT}})_3}[1 - G((R)_z)]$. However, by definition of truncated distribution, $G_1(z) = G_2(z) = G_3(z)$, if $z > \frac{-\left(\mu-(I_{\mathrm{M}}^*)_3\right)}{\sigma_{\mathrm{M}}}$. Thus, the property of the standardized loss function still holds for $n = 3$. Moreover, $\frac{\partial L\left(t,\left((I_{\mathrm{MF}}^*)_n-(I_{\mathrm{D}})_n\right)_z\right)}{\partial (I_{\mathrm{D}})_n} = \frac{1}{(\sigma_{\mathrm{FT}})_n}\left(1 - G_n\left(\frac{(I_{\mathrm{MF}}^*)_n-(I_{\mathrm{D}})_n-\mu_n}{\sigma_{\mathrm{M}}}\right)\right)$ and $\frac{\partial^2 L\left(t,\left((I_{\mathrm{MF}}^*)_n-(I_{\mathrm{D}})_n\right)_z\right)}{\partial^2 (I_{\mathrm{D}})_n} = \frac{1}{{(\sigma_{\mathrm{FT}})_n}^2} g_n\left(\frac{(I_{\mathrm{MF}}^*)_n-(I_{\mathrm{D}})_n-\mu_n}{\sigma_{\mathrm{M}}}\right) \geq 0$. Therefore, F.O.C of $\mathrm{E}[(\pi_{\mathrm{FT}})_n]$ w.r.t. $(I_{\mathrm{D}})_n$ gives $(I_{\mathrm{D}}^*)_n = (I_{\mathrm{MF}}^*)_n - \left((\sigma_{\mathrm{FT}})_n G_n^{-1}\left(1 - \frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})}\right) + \mu_n\right)$. By definition, $0 \leq (I_{\mathrm{D}})_n \leq (I_{\mathrm{MF}}^*)_n$. Thus, $(I_{\mathrm{D}}^*)_n = \max\left(0,(I_{\mathrm{MF}}^*)_n - \left((\sigma_{\mathrm{FT}})_n G_n^{-1}\left(1 - \frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})}\right) + \mu_n\right)^+\right)$. Therefore, FT's optimal inventory level under mechanism n is given by

$$(I_{\mathrm{FT}}^*)_n = \max(0,(I_{\mathrm{MF}}^*)_n - (I_{\mathrm{D}}^*)_n)$$

■

Appendix G: Proof of Proposition 7

Proof 7. When $I_{\mathrm{FT}}^{*} > 0$, for I_{FT}^{*},

$$\frac{\partial}{\partial\beta}\left(1-\frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(p-p_{\mathrm{ST}})}\right)=\frac{(1-\beta+h_{\mathrm{FT}})\beta s_{\mathrm{FT}}-(\beta+h_{\mathrm{FT}})(1-\beta)p}{\left(\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(p-p_{\mathrm{ST}})\right)^{2}}<0$$

, since $\frac{p}{p_{\mathrm{ST}}} > \frac{1-\beta+h_{\mathrm{FT}}}{1-\beta}$ and $p_{\mathrm{ST}} > s_{\mathrm{FT}}$ (thus numerator is negative). For $(I_{\mathrm{FT}}^{*})_n$, if $(I_{\mathrm{D}}^{*})_n \geq 0 \Leftrightarrow (I_{\mathrm{FT}}^{*})_n = (I_{\mathrm{MF}}^{*})_n - (\sigma_{\mathrm{FT}})_n G_n^{-1}\left(1-\frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})}\right)+\mu_n \geq 0$, $(I_{\mathrm{FT}}^{*})_n = (\sigma_{\mathrm{FT}})_n G_n^{-1}\left(1-\frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})}\right)+\mu_n$. But,

$$\frac{\partial}{\partial\beta}\left(1-\frac{(h_{\mathrm{FT}}+\beta)p_{\mathrm{ST}}-\beta s_{\mathrm{FT}}}{\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})}\right)=\frac{-(v-p)\left(\beta(p-s)+p_{\mathrm{ST}}h_{\mathrm{FT}}+(1-\beta)\right)}{\left(\beta(p_{\mathrm{ST}}-s_{\mathrm{FT}})+(1-\beta)(v-p_{\mathrm{ST}})\right)^{2}}<0$$

, since $v > p$. Therefore, I_{FT}^{*} and $(I_{\mathrm{FT}}^{*})_n$ as the ST disruption likelihood $1-\beta$ increases, when $I_{\mathrm{FT}}^{*} > 0$ and $(I_{\mathrm{D}}^{*})_n \geq 0$, respectively. However, if $(I_{\mathrm{D}}^{*})_n = 0 \Leftrightarrow (I_{\mathrm{FT}}^{*})_n = (I_{\mathrm{MF}}^{*})_n$, by Proposition 4, $(I_{\mathrm{FT}}^{*})_n$ could increase or decrease as the ST disruption likelihood $1-\beta$ increases. ■

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ESSAY 3

RISK MANAGEMENT STRATEGIES IN TRANSPORTATION CAPACITY DECISIONS: AN ANALYTICAL APPROACH

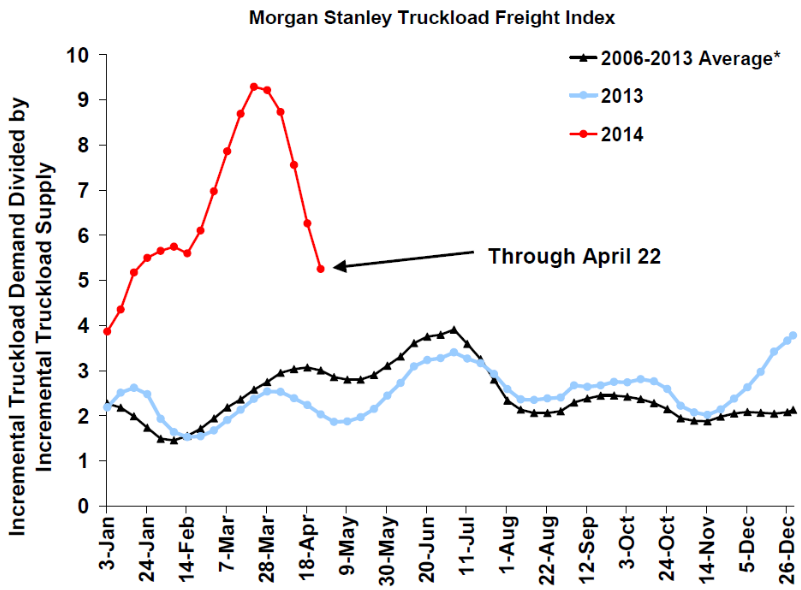
Abstract

In recent years, access to freight transportation capacity has become a constant issue in the minds of logistics managers due to capacity shortages. In a buyer-seller relationship, reliable, timely, and cost-effective access to transportation is critical to the success of such partnerships. Given this, guaranteed capacity contracts with 3PLs may be appealing to shippers to increase their access to capacity and respond effectively to customer requirements. With this new opportunity, 3PLs must focus on approaches that can assist them in analyzing their options as they promise guaranteed capacity to shippers when faced with uncertain demand and related risks in transportation. In this paper, we analytically analyze three capacity-based risk mitigation strategies and the mixed use of these individual strategies using industry based data to provide insights on which strategy is preferable to the 3PL and under what conditions. We posit that the selection of a strategy is contingent on several conditions faced by both the shipper and the carrier. Although our approach is analytical in nature, it has a high degree of practical utility in that a 3PL can utilize our decision models to effectively analyze and visualize the trade-offs between the different strategies by considering appropriate cost and demand data.

1. Introduction

Supply chain risk management (SCRM) is receiving increased attention in recent years. Much of the literature in this area focuses on manufacturers and retailers (Tang, 2006; Snyder et al., 2010; Ho et al., 2015). However, several recent trends justify the need for SCRM research focusing on transportation services in a supply chain context due to the emphasis on maintaining strong buyer-supplier relationships. In the context of the current paper, we specifically focus on risk management strategies for transportation capacity management, which may have a significant impact on buyer-supplier relationships as transportation capacity shortage can result in increased costs and reduced level of on-time deliveries. Sourcing for transportation services in this setting has important implications to the literature in the domain of buyer-supplier relationships, where the buyer is the shipper and the seller is either a 3PL/4PL acting as an intermediary. In such a context, risk management strategies for transportation capacity management used by the 3PLs, as sellers, become critical in building sustained relationships with their buyers. The risk management strategies presented in this paper are applicable, for the most part, to both shippers who are operating or considering operating a private fleet and third party logistics providers (3PLs) that provide transportation services to shippers.. This is especially critical for buyer-supplier relationships that operate in a just-in-time environment where shipments have to be received in a timely manner and any unexpected delays can cause severe disruptions in effectively meeting customer demands.

Recent industry studies and data demonstrate that demand for trucking is increasing more rapidly than the capacity increase. Morgan Stanley's dry van truckload freight index indicates a market that has recently experienced record capacity tightness as seen in Figure E3-1[6].



The index measures the incremental demand for Dry-Van Truckload services compared to the incremental supply. When a given reading is above prior years' level, it means there is more freight demand relative to available capacity. When a given reading is below prior years' level, it means there is less freight demand relative to capacity. *2006-2013 average trend line excludes financial crisis years of 2008 and 2009

Figure E3-1: Morgan Stanley's dry van truckload freight index

According to the *Transplace's CEO Blog* on March 28, 2014, this capacity tightness can be attributed to prolonged extreme winter weather, shortage of intermodal capacity, stricter Hours-of-Service regulations, and the economic recovery. From a shipper's perspective, the potential cost of not having access to transportation capacity can be very high. For example, an auto assembly plant maintains two to four hours' worth of materials in general. If the delivery of a certain material used in the assembly line delays and does not arrive until the safety stock is depleted, the assembly line will be shut down. Ac-

[6] Please note that materials that are referenced comprise excerpts from research reports and should not be relied on as investment advice. This material (Figure E4-1) is only as current as the publication date of the underlying Morgan Stanley (MS) research. Additionally, MS has provided their materials here as a courtesy. Therefore, MS and the authors do not undertake to advise you of changes in the opinions or information set forth in these materials.

cording to Business Forward Foundation 2014[7], each hour of down time of an auto assembly plant costs approximately $1.25 million.

Although the capacity shortage has taken a downturn, the recent upswing may not completely fade as some of the aforementioned reasons may continue placing pressure on trucking capacity moving forward. This issue was predicted in September 2013 by Bob Costello, chief economist of the American Trucking Associations, while he was speaking at TMW Systems' Transforum 2013 user conference, where he said "we are headed for a capacity problem. The industry is not adding much capacity today."[8]

3PLs are one of major components of today's supply chains. Companies in various industries have been outsourcing their logistics activities to achieve more effective and efficient supply chains. There is a tendency for more shippers to outsource some portion of their transportation and logistics to 3PLs. The 2010 Global 3PL & Logistics Outsourcing Strategy survey by Eye-for-Transport presents the finding that 97% of shippers intend to increase their use of 3PLs in the future. As a result, the 3PL market becomes one of continuously growing industry segments. Over the last 20 years, outsourcing to 3PLs has grown about three times faster than the GDP, and in 2012, 3PLs' gross revenue in US was $141.8 billion (Armstrong & Associates, Inc., 2013[9]).

Among the logistics activities outsourced, the majority are the transportation activities (Power et al., 2007). About 73% of total 3PLs' gross revenue ($103 billion out of $141.8 billion) in US is contributed by transportation activities (Armstrong & Associates, Inc., 2013). Thus, in today's volatile supply chain environment, one of the major chal-

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[7] http://www.businessfwd.org/SevereWeatherAndManafacturingInAmerica.pdf
[8] http://www.truckinginfo.com/channel/fleet-management/news/story/2013/09/ata-economist-industry-faces-capacity-crunch.aspx?prestitial=1
[9] http://www.3plogistics.com/3PLmarketGlobal.htm

lenges 3PLs face is risk management due to demand uncertainty. In majority of the manufacturing and service industries, there is inherent demand uncertainty, which creates the same level of uncertainty in the demand for transportation services. Moreover, because of the increased capacity shortage in transportation industry, transportation costs can be very high and the availability of capacity options may be a major problem for shippers. Given this, shippers are constantly looking for ways to mitigate the risk of high transportation costs in the face of demand variability and capacity shortage.

Traditionally, there are three types of relationships between transportation carriers and shippers. The first type is “dedicated”, where a shipper charters trucks from a carrier for long-term and becomes the only user of these trucks. The second type is “contract” arrangement, where shipper and carrier agree on a price list for the services but there is no capacity guarantee. The third type is the “spot” market, where capacity availability and rates are determined by the supply-demand dynamics in the transportation marketplace at any point in time. A fourth type that has been discussed in a few studies is the use of transportation options (Tsai et al., 2009; Tibben-Lembke and Rogers, 2006), similar to the real options in stock and commodity markets, where a shipper would buy a transportation option from a carrier, which would give the shipper the right but not the obligation to send a shipment in a particular freight lane at a specified future time for a specified future cost. This new type of contracting guarantees capacity in exchange for higher rates and/or upfront reservation payment for the transportation option.

In our recent discussions with two shippers, one manufacturer and one service provider, we learned that both firms have had an interest in engaging in a transportation option contract with their preferred carriers. The manufacturer firm is currently piloting such a contract arrangement with a truckload carrier, where the carrier guarantees capacity for a number of trucks in exchange for rates higher than regular contracts. Similarly, SGA Production Services, which provides seating and staging solutions for entertainment events, has explored considering such an agreement with their preferred carrier to have access to guaranteed capacity due to carrier's high quality service. As a shipper in services industry, the transportation service quality and access to capacity in a timely manner is essential to their business. Recently, their preferred carrier has sub-contracted their shipments to other carriers more often than usual, which can be interpreted as a shortage of capacity in the premium transportation services SGA uses. These examples demonstrate that there are shippers, both in manufacturing and services, which are in search for new ways of contracting in the face of the transportation capacity crunch, which creates higher and more volatile rates in the marketplace. In that context, we study the transportation capacity and risk management strategies from a 3PL's perspective, when such a carrier is contracting with a shipper with guaranteed capacity. We build an analytical framework and related decision models to understand the effectiveness of 3PLs' transportation capacity management strategies (TCMS) in the face of demand uncertainty while providing guaranteed capacity.

This study is mostly tailored towards small to medium size 3PLs providing truckload services due to several reasons. First, for small carriers, even the addition of a single, sufficiently large customer may require the carrier to make capacity management decisions. This makes the problem not a rare but a recurring issue for such carriers. Second, capacity management decisions can have a bigger impact on the financial health of a small carrier compared to a large carrier. Third, capacity decisions of truckload carriers in contrast to less-then-truckload carriers, such as buying new equipment or outsourcing, can be made in near-isolation without much impact on the use of existing equipment. Fourth, less-than-truckload carriers, given their business model, serve multiple customers with small loads on the same trucks through a series of consolidation and deconsolidation activities performed at multiple terminals and the use of multiple trucks. Thus, addition of a new customer usually has a less drastic effect. In case of a major impact, the capacity decisions are much more complicated than the truckload case as it involves a multitude of linked terminals, trucks traveling between these terminals on schedules, etc. Fifth, in United States, most of the carriers can be considered small and medium size since 97% of all truckload carriers operate 20 or fewer trucks[10], which accounts for about 20% of total revenue[11], thus making this very relevant to a significant portion of the industry that do not have the capability of developing this type of scientific methods for analysis.

We consider three risk mitigation strategies, where the 3PLs take some actions in advance of the demand realization, as presented in Table E3-1. Reserving a portion of 3PL's available internal capacity (*RIC*) for the customer is the first strategy. The fixed cost of *RIC* is the lost profit that was sacrificed by reserving this capacity for this new customer. The variable costs (fuel, maintenance etc.) are proportional to the use of the equipment. Increasing 3PL's own internal transportation capacity (*IIC*) is the second mitigation strategy and this incurs a fixed upfront capital cost as well as some other costs (insurance etc.) regardless of what level of demand is realized. The variable costs (fuel, maintenance etc.) of *IIC* are proportional to the use of the equipment. The last strategy is paying a reservation fee in return for guaranteed capacity (*REC*), which is also known as

[10] http://web.archive.org/web/20080409065529/
http://www.whitehouse.gov/OMB/inforeg/2003iq/175.pdf
[11] http://www.ops.fhwa.dot.gov/Freight/publications/eval_mc_industry/index.htm

transportation options (Tsai et al., 2009; Tibben-Lembke and Rogers, 2006). This reservation cost is an upfront fixed cost that is proportional to the reserved capacity and incurs an additional exercise cost proportional to the use of the reserved capacity after demand realization.

Table E3-1: TCMS for 3PLs

Strategy	Description
Reserving Internal Capacity (*RIC*)	Dedicate some of the equipment to the customer
Increasing Internal Capacity (*IIC*)	Buy or lease transportation equipment
Reserving External Capacity (*REC*)	Reserve guaranteed external capacity through subcontracting

It is easy to see that two of these strategies can also be used by a shipper facing a transportation capacity shortage and/or increased level of volatility in transportation rates in the spot market. In that context, a shipper may consider investing in a private fleet (*IIC*), or contracting with a 3PL for guaranteed capacity (*REC*). Since all shippers are competing for the shrinking transportation capacity, this type of analysis becomes very relevant to shippers as well as carriers.

The rest of the paper is organized as follows. In section 2, we review the related literature in the areas of SCRM, capacity planning, transportation planning, and 3PLs. Following which we develop an analytical model for representing 3PL's TCMSs and present related analyses. Finally, we address the managerial implications of our research, limitations of our approach, and directions for future research.

2. Literature Review

The proposed research is closely related to four streams of literature: SCRM, capacity planning, transportation planning and 3PL. In the following sections we briefly review the key literature in each of these streams by highlighting the associated gaps.

2.1. Supply Chain Risk Management

SCRM is defined as “the management of supply chain risk through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity” (Tang, 2006). In supply chain management (SCM) literature, risk has been addressed mainly on manufacturing processes and demand uncertainty (e.g., Zipkin, 2000). Naylor et al. (1999) show that the combination of agile and lean manufacturing can postpone the decoupling point and reduce the risk of being out of stock under demand uncertainty. Gupta and Maranas (2003) propose a stochastic programming based bi-level optimization model for manufacturing and distribution timing decisions in order to achieve cost reduction under demand uncertainty. Moreover, vast literature considers safety stocks and warehouses between manufacturers and retailers as the means to reduce the effect of demand and lead-time uncertainties (Axsäter, 1993; Federgruen, 1993; Inderfurth, 1994, van Houtum et al., 1996; Diks et al., 1996; Schwarz, 1989; Schwarz and Weng, 2000).

In addition, more recently, supply uncertainty has become another main issue in SCRM. The studies of supply uncertainty mainly consist of two approaches: i) supply disruption model and ii) random-yield model. In the supply disruption model (e.g., Snyder et al., 2010), a supplier’s status is either “up” or “down”: “up” means that the orders are fulfilled in full and on time, and “down” means no order can be fulfilled. Parlar and Perry (1995) and Parlar (1997) consider random supply disruptions by applying Markov Chain models with stochastic demand and lead-times under different inventory policies. Tomlin (2006) also applies a Markovian approach to present supplier's availability with consideration of disruptions characteristics: high impact but short and low impact but long. In a random-yield model, it is assumed that the supply level is a random function of the input level (e.g., Yano and Lee, 1995; Grosfeld-Nir and Gerchak, 2004). Graves (1987) provides a survey of many analytical models of determining production and inventory policies under this assumption with emphasis on random demand. He and Zhang (2008) focus on the random yield effects on the performance of all parties in a supply chain in a single supplier and single retailer context. Gurnani et al. (2000) consider random yields of supply in order to minimize costs and derive bounds for the cost function values.

To the best of our knowledge most of the existing publications on SCRM are addressed from a manufacturers' standpoint and thus focus on production processes and functions. However, as Tang (2006) points out, transportation planning in terms of when and which type of transportation model to utilize needs to be examined in designing supply chains to mitigate risks. Moreover, several researchers argue that demand uncertainty combined with information distortion in a supply chain can cause many serious problems such as insufficient transportation capacity (Lee et al., 1997; Tang, 2006). While the importance of transportation decisions from the standpoint of managing risks is addressed in the literature, formal decision models that allow companies to appease risks in this context need further development.

2.2. Capacity Planning

The issue of capacity planning is well researched and has been dealt with in various settings. In capacity planning literature, capacity expansion and its allocation is the main focus (e.g., Singh et al., 2012; Liu and Papageorgiou, 2013). Birge (2000) considers the capacity planning models in order to assess the allocation of newly installed capacity in an environment characterized by limited resources and demand uncertainty. He considers a decision regarding whether to install additional capacity at the manufacturing plant level. Huh et al. (2006) determine the sequence and timing for purchasing and retiring machines in a manufacturing environment under demand uncertainty. Okubo (1996) studied capacity reservation in manufacturing with consideration of inventory. Serel et al. (2001) and Serel (2007) also considered capacity reservation combined with inventory issue from a real options perspective in manufacturing. They characterized supplier's own capacity reservation with single period newsvendor problem. While inventory can play a prominent role in capacity planning in manufacturing, it is not possible to hold inventory in a transportation capacity planning setting. This makes the capacity planning problem considered in this paper different from manufacturing capacity planning.

Other service industries have also shared the infeasibility of keeping inventory as an option. From such a perspective, human resource planning focuses on the assignment of the right number of staff at the right place and time for a given demand. Agnihothri and Taylor (1991) use a queuing model to find the optimal staffing levels at a hospital call-center. Mason and Ryan (1998) apply heuristic algorithms and simulation for the Customs staffing problem at an airport. Duder and Rosenwein (2001) consider the staffing problem in call-centers and show that by using simple formulas it is possible to increase service metrics. Adenso-Diaz et al. (2002) develop a model that permits the calculation of the minimum staff needed to carry out all the functions correctly within a service while guaranteeing an expected level of quality.

Physical capacity planning is also an area of research for service industries such as healthcare and entertainment. Green and Nguyen (2001) apply a queueing model approach to the hospital bed planning problem to gain insights on the potential impact of cost-cutting strategies on patients' delays for beds. Zhang et al. (2012) integrate demographic and survival analysis, discrete event simulation, and optimization for setting long-term care capacity levels over a multiyear planning horizon to achieve target wait time service levels. To estimate the required number of rides in a theme park, Wanhill (2003) provides a closed-form solution integrating the market population, demand fluctuations, and average ride throughput. Using aggregate operation statistics of hotels, Gu (2003) employs a single-period inventory model to estimate the optimal room capacity for hotels.

While each of the aforementioned methods have their own relative advantages and disadvantages from the standpoint of capacity planning and management, the area of transportation capacity management as evident from above has received very little attention. It is also important to note that the above discussed methods do not specifically address the risk management issues related to capacity planning, which is the focus of our approach. In this context, we evaluate the expected profit of alterative capacity management options and compare the closed form solutions over different levels of demand variability from a risk mitigation standpoint. This type of an analysis allows us to pinpoint the effectiveness of each alternative under certain conditions, which to our knowledge has not been addressed in this domain. We also consider a real options approach that lends itself to this type of an analysis.

2.3. Transportation Planning

A number of supply chain researchers recognize the importance of transportation issues since manufacturers in practice increasingly try to integrate production and transportation planning in order to optimize both processes simultaneously. Jung et al. (2008) develops linear programming models that consider production and transportation planning in a study of external environmental contingency effect. Park (2005) suggests a mixed integer linear programming model composed of multi-site, multi-retailer, multi-product, and multi-period environment. He integrates production and transportation planning by presenting production planning sub-model whose outputs become the input to another sub-model focusing on transportation planning. Ekşioğlu et al. (2007) also present a mixed integer linear programming model that integrates production and transportation planning with consideration of multi-period, multi-product, and multi-site environment. However, in most of these cases, transportation is considered as a product distribution resource (i.e., supplement to production planning).

There are a few papers that indirectly show that the transportation issues need to be addressed at the same level as production. Chen and Lee (2004) consider transportation in part with production by employing a multi-objective mixed integer nonlinear programming model for optimizing supply chain networks. Yildiz et al. (2014) treat transportation as strategically interrelated but physically separated entity in reliable supply chain network design. They assume that the transportation entities can make their own decisions on capacity. However, the focus of these studies is still primarily manufacturing oriented.

As stated earlier, companies in various industries have been outsourcing their transportation activities to 3PL for achieving more effective and efficient supply chains. In addition, given that 3PL market represents a large portion of nation’s economy, studies that focus on transportation issues from a 3PL's perspective (beyond manufacturing focused view) are essential.

2.4. Third Party Logistics Services

Based on Leuschner et al. (2014), 3PL research can be characterized as consisting of three eras. The first era is comprised of descriptive works that capture the logistics outsourcing phenomenon. The research in this era examines the motives for outsourcing and challenges/opportunities for improved logistics outsourcing (e.g., Lieb, 1992; Lieb and Bentz, 2005a; Sink et al., 1996). The second era is composed of the refinement of key concepts, the establishment of hypothesis testing, and a stronger orientation toward explanation and normative prescription. The works in the second era explore the characteristics of successful outsourcing arrangements (e.g., Daugherty et al., 1996; Sink and Langley, 1997) and the outcomes from logistics outsourcing (e.g., Stank et al., 1996). The third era focuses on the implementation and replication of logistics outsourcing studies conducted in North America to Western Europe, Asia, and Australia. Related research in this area not only focuses on common practices across countries but also strives to understand differences in practices based on cross-national studies (e.g., Bookbonder and Tan, 2003; Wang et al., 2008).

However, as Ellram and Copper (1990) define, 3PL is "outside parties who provide shippers with functions not performed by the firm", which implies that 3PL needs to be studied from its own standpoint. Lieb and Randall's (1996) and Lieb and Bentz's (2005b) research address issues from a 3PLs perspective but these studies are limited to descriptive analysis. Ülkü and Bookbinder (2012) consider 3PL operations but their study focuses on order consolidation which is highly dependent on capacity decisions and can only be performed after capacity level is decided (they assume that the capacity is unlimited).

3. Models for 3PL's Risk Mitigation Strategies

We consider a single period problem where the 3PL faces symmetric random demand D for guaranteed capacity service over the coming period with probability density function $f(D)$ with mean μ_D and standard deviation σ_D. In this setting, each strategy k has a unit fixed cost (c^{ST_k}) and a unit variable cost (c^{V_k}), where ST_k is the k^{th} strategy in $ST = \{IIC, REC, RIC\}$. Notice that both of these costs are unit costs that are based on industry averages, which are calculated on a per mile basis. Thus, the fixed cost of capacity expansion practically becomes a variable cost in our analysis since (c^{ST_k}) is calculated based on the industry-wide annual usage of these assets and the actual fixed cost of the assets over their lifetime. This justifies our use of a single period model, which involves the selection of capacity related risk mitigation strategies that naturally have multi-period implications.

The fixed cost of strategy k is $c^{ST_k}I^{ST_k}$, where I^{ST_k} is the capacity allocation for guaranteed capacity service in strategy k and it is incurred irrespective of the realized mand D. If $D < I^{ST_k}$, the 3PL can satisfy shipper's order by using the capacity prepared by strategy k. On the other hand, if $D > I^{ST_k}$, the 3PL cannot fully satisfy shipper's demand. Because of this, the quantity that is actually shipped is $\min\{D, I^{ST_k}\}$. For every unit shipped, the 3PL currently spends unit variable cost c^{V_k} and earns r^S of unit revenue with its existing contractual non-guaranteed capacity customers. In comparison, the 3PL will charge $r^G > r^S$ of unit revenue for the guaranteed capacity service. Although the 3PL guarantees capacity in this arrangement, there is always a positive probability that the

3PL will be unable to ship all the demand of the shipper. In that case, we assume that the 3PL pays a unit penalty cost to the shipper for every unshipped unit. This penalty cost can be a fixed contractual penalty. It can also be the high cost of subcontracting the shipment to a carrier via spot market. We assume that, the upfront investment needed for the *IIC* and *REC* strategies may be restricted by a budget.

With the aforementioned assumptions, the expected profit of the 3PL using strategy k is given by

$$E[\pi^{ST_k}] = -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^\infty \min(x, I^{ST_k})\, dF(x)$$
$$- c^{penalty} \int_{I^{ST_k}}^\infty (x - I^{ST_k})\, dF(x)$$

where $F(x)$ is cumulative density function of demand x. In this function, the first term is the fixed cost of using strategy k. The second term is the revenue minus the variable cost for the amount shipped. The last term is the penalty cost for the unshipped demand. Under a budget constraint, the 3PL wants to maximize its expected profit using a risk mitigation strategy k (ST_k):

$$\max\ E[\pi^{ST_k}]$$

$$\text{subject to} \quad c^{ST_k} I^{ST_k} y_k \leq B$$

$$\text{where} \quad y_k = \begin{cases} 1, & \text{for } IIC \text{ and } REC \\ 0, & \text{for } RIC \end{cases}$$

where B is the budget amount. Notice that the budget constraint is not relevant for *RIC* as there is no initial investment for that strategy and variable y_k is used to as an indicator for that.

Using this expected profit, we can find the optimum level of capacity allocation by taking the derivative of this function. The following proposition provides this result.

Proposition 1. With given cost and price parameters for strategy k, the optimal capacity level allocated for the shipper is given by

$$I^{ST_k^*} = \max\left(0, \min\left(\frac{B}{y_k c^{ST_k}}, \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x\right)\right)$$

Proof is provided in Appendix A.

Proposition 1 indicates to us that the optimal capacity is highly affected by costs, prices, and demand uncertainty. However, it does not imply that strategy k at $I^{ST_k^*}$ always increases expected profit, i.e., strategy k can also reduce expected profit. Intuitively, when $I^{ST_k^*} = 0$, strategy k for guaranteed delivery contract will reduce expected profit of carrier due to penalty cost. When budget B is not sufficient to acquire the optimum capacity level that maximizes the expected profit, the 3PL acquires the most capacity that's allowed by B. We next analyze the profitability of strategy k when $I^{ST_k^*} > 0$.

Theorem 1. With given cost and price parameters for strategy k, the strategy increases profit if

a) $\frac{r^G - c^{V_k} - c^{ST_k}}{\omega^{ST_k}\left(f_S\left(I_S^{ST_k^*}\right)\right)} \geq \frac{\sigma_x}{\mu_x}$, when $I^{ST_k^*} = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{\omega^{ST_k}}\right) + \mu_x$

b) $\frac{r^G - c^{V_k}}{\omega^{ST_k}\sigma_x l\left(x, I_S^{ST_k^*}\right)} \geq \frac{\sigma_x}{\mu_x}$, when $I^{ST_k^*} = \frac{B}{y_k c^{ST_k}}$

where $\omega^{ST_k} = r^G - c^{V_k} + c^{penalty}$

Proof is provided in Appendix A.

Theorem 1 shows that the budget plays a critical role in strategy k's profitability as well as cost and price parameters under demand uncertainty. We use Proposition 1 and Theorem 1 in the upcoming subsections as we analyze the different mitigation strategies.

3.1. Reserve Internal Capacity

Reserving the internal capacity strategy has the advantage that the 3PL does not need to make any additional investment. Thus, essentially the budget for investment (B) is zero. But, this does not mean that there is no fixed cost of this strategy. When the 3PL decides to reserve some of its existing capacity as part of the guaranteed capacity contract, it no longer earns its standard revenue r^S from those reserved units. Thus, there is an opportunity cost, which is incurred regardless of whether the reserved capacity is used for the new contract or not. However, since the variable cost ($c^{O\text{-}variable}$) is incurred only when the service is provided, the true opportunity cost of this reservation is $r^S - c^{O\text{-}variable}$, which we treat as the unit fixed cost (c^{RIC}) of the *RIC* strategy. To investigate how the expected cost function behaves, we chose the cost parameters using industry-based estimates. Based on the data from a report publish by American Transportation Research Institute in 2012[12], the fixed cost of a trucking company is about 17% of its total cost and the remaining 83% is the variable costs. According to a recent *Forbes* article[13] the average profit margin of trucking companies is about 6%, which implies that the total cost is 94% of the revenue. Using these industry statistics, we derive the following relationships for the costs of *RIC* strategy:

$$c^{O\text{-}variable} = 0.94 \cdot 0.83 \cdot r^S = 0.78 \cdot r^S \text{ and } c^{RIC} = r^S - c^{O\text{-}variable} = 0.22 \cdot r^S$$

Since the 3PL guarantees capacity to the shipper, we stipulate a very high penalty cost for illustrative purposes, where $c^{penalty} = 1.5 \cdot r^G$. Thus, the penalty cost is 50% more than the service price. For ease of presentation, we set $r^S = 1$, as we plot the expected profit and capacity allocation functions in the graphs. Using these parameters, in Figure E3-2, we see how the expected profit function for the *RIC* strategy behaves as

[12] http://www.glostone.com/wp-content/uploads/2012/09/ATRI-Operational-Costs-of-Trucking-2012.pdf
[13] http://www.forbes.com/sites/sageworks/2014/02/20/sales-profit-trends-trucking-companies/

both demand variability and service rate parameters change. The demand variability is captured by the coefficient of variation (cv), which is a more robust measure compared to standard deviation. At $cv = 0$, mean demand $(\mu_x) = 10$ and standard deviation $(\sigma_x) = 0$, thus there is no variability. The cv value is increased to investigate the behavior of the total profit functions under increased demand variability. Each of the lines represent a different guaranteed capacity service rate r^G. *In all three rates, as demand uncertainty increases the expected profit decreases at a decreasing rate*. When guaranteed capacity rate is only 10% more than the standard contractual rate ($r^G = 1.1$), the expected profit function takes negative values beyond the slightest demand variability (at $cv \sim 0.22$). Whereas, with a 50% difference in the rates ($r^G = 1.5$), the expected profit always stays positive, although it approaches zero at high demand variability (at $cv > 0.8$). This type of an analysis is useful in understanding the relationship between expected profits, demand uncertainty (cv), and service price (r^G).

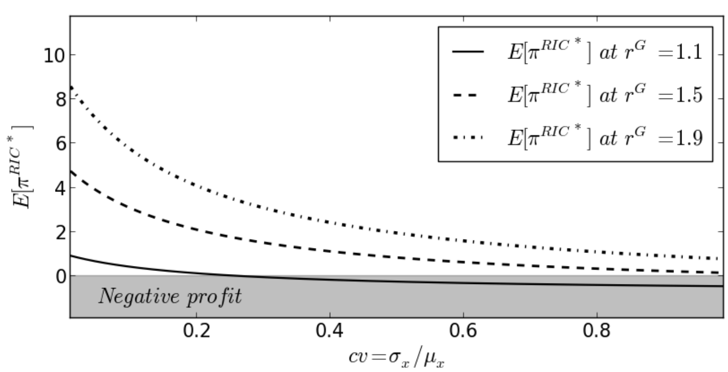

Figure E3-2: *RIC* strategy expected profit at different risk levels and service prices

From a managerial standpoint, the above analysis allows the 3PL decision-makers to set service price in an effective manner given the level of uncertainty that is faced in maximizing expected profits. A series of such experiments can be run in understanding the threshold values for service rates that can be effectively employed in shipper-carrier negotiations in setting appropriate contractual parameters. To the best of our knowledge, such an analysis has not been undertaken in this context in the extant literature.

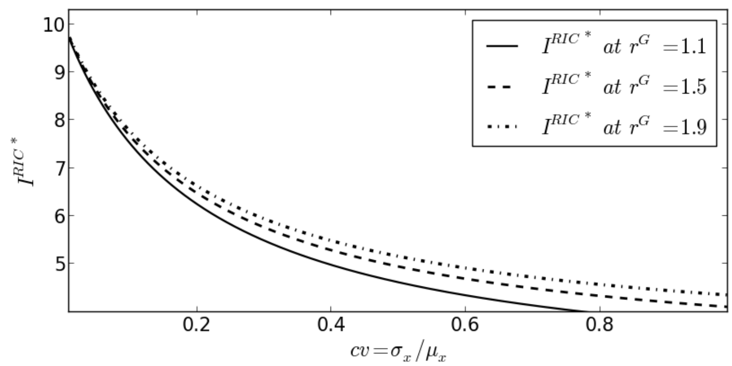

Figure E3-3: *RIC* strategy capacity allocation at different risk levels and service prices

Similarly, we can see how the optimum capacity allocation value ($I^{ST_k{}^*}$), derived in Proposition 1 behaves, as both demand variability and price parameters change in Figure E3-3. In this graph, as demand variability increases, the capacity allocation level decreases at a decreasing rate. When there is no uncertainty, $cv = 0$, $I^{RIC^*} = \mu_x = 10$. As we decrease the service price, the graph shifts downwards, resulting in lower I^{RIC^*} levels.

Proposition 2.

a) $I^{ST_k{}^*}$ is decreasing in c^{ST_k} but not affected by c^{V_k}, when budget is not sufficient.

b) $I^{ST_k{}^*}$ is decreasing in both c^{ST_k} and c^{V_k}, when budget is sufficient and $I^{ST_k{}^*} > 0$. The impact of c^{ST_k} is greater than c^{V_k}.

Proof is provided in Appendix A.

Figure E3-4 & E3-5 illustrate how the optimum internal capacity reservation amount behaves as both demand variability and cost parameters change. In both graphs, as we increase the cost parameters, the graph shifts downwards, resulting in lower $I^{ST_k{}^*}$ levels. This is more visible in Figure E3-4, *which shows that significant changes in the fixed cost have higher impact than changes in variable costs*. This is due to the fact that the fixed costs are incurred regardless of whether the reserved capacity is used or not, whereas the variable costs are incurred only when the capacity is used.

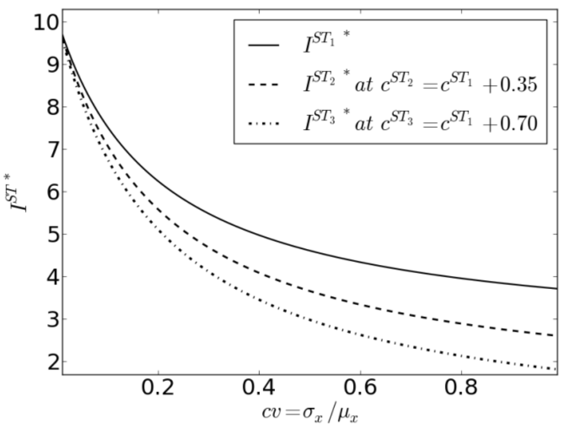

Figure E3-4: Impact of fixed cost changes

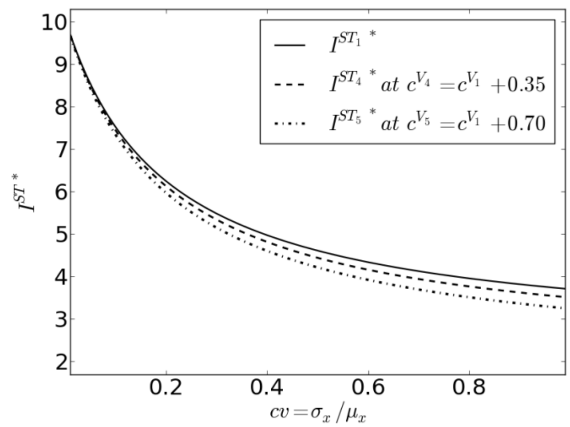

Figure E3-5: Impact of variable cost changes

The main takeaway from these analyses and the results in Figure E3-3, E3-4, and E3-5 is that, from a managerial perspective it sheds light on the optimal capacity allocation that the 3PL should consider under conditions of risk, service rates, fixed and variable costs. Given a certain environment, the decision-maker can utilize our approach in solving for the optimal capacity allocation that maximizes profits. In addition, the general direction of the relationships depicted above allows the decision-maker to set service prices and capacity allocations in an effective manner.

3.2. Increase Internal Capacity

When the 3PL is willing to make an upfront investment with a positive budget B, then it faces a capacity expansion problem. In order to meet the demand of the shipper for guaranteed capacity, the 3PL can use its existing assets by reserving some of it for the shipper (the *RIC* strategy), as analyzed in the previous section. Alternatively, the 3PL can also expand its capacity by acquiring new assets (the *IIC* strategy), which has a fixed cost of new equipment acquisition. With the new equipment, we assume 5% efficiency gain in variable costs[14]. Thus, the variable cost of *IIC* is slightly lower than *RIC*. The fixed cost of *IIC* is calculated using the same industry statistics, which indicates that 17% of the costs are attributed to fixed costs. With these assumptions we have the following variable and fixed costs for *IIC* strategy.

$$c^{N\text{-}variable} = 0.94 \cdot 0.83 \cdot 0.95 \cdot r^S = 0.74 \cdot r^S \text{ and } c^{IIC} = 0.94 \cdot 0.17 \cdot r^S = 0.16 \cdot r^S$$

3.3. Reserve External Capacity

In the context of guaranteed transportation capacity contracts, we also include the use of transportation put options, where the 3PL pays an upfront reservation price (c^{REC}) to another carrier in return for a guaranteed capacity at a certain exercise price ($c^{exercise}$) in the future. Similar to the *IIC* strategy, this strategy also requires an upfront investment. Thus, it is only applicable when the budget B is positive. While there is no such transportation option market in reality, it is certainly a possibility for future options developments in the industry. Since there is no industry data that can be used for this phase of the analysis, we use hypothetical parameters for this strategy for illustrative purposes. The parameters are chosen so that the *REC* strategy has a low fixed cost and high variable cost.

3.4. Selecting the Best Risk Mitigation Strategy

Comparing two strategies when there is a budget constraint is not trivial. The following theorem provides a parametric comparison between two strategies.

Theorem 2. Under given parameters, strategy i is better than strategy j

a) When budget is sufficient for both strategies,

---

[14] We assume that a new truck can gain cost efficiency compared to an old truck from higher fuel economy, new tires, etc.
https://www.ceres.org/trucksavings
http://www.goodyeartrucktires.com/pdf/resources/publications/Factors%20Affecting%20Truck%20Fuel%20Economy.pdf

i. If $\frac{\omega^{ST_i}-\omega^{ST_j}+c^{ST_j}-c^{ST_i}}{\omega^{ST_i}\cdot f_S\left(I_S^{ST_i*}\right)-\omega^{ST_j}\cdot f_S\left(I_S^{ST_j*}\right)} > \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i*}\right) > \omega^{ST_j} \cdot f_S\left(I_S^{ST_j*}\right)$

ii. If $\frac{\omega^{ST_i}-\omega^{ST_j}+c^{ST_j}-c^{ST_i}}{\omega^{ST_i}\cdot f_S\left(I_S^{ST_i*}\right)-\omega^{ST_j}\cdot f_S\left(I_S^{ST_j*}\right)} < \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i*}\right) < \omega^{ST_j} \cdot f_S\left(I_S^{ST_j*}\right)$

b) When budget is not sufficient for both strategies,

i. If $\frac{\omega^{ST_i}-\omega^{ST_j}}{\omega^{ST_i}\cdot l\left(x,I_S^{ST_i*}\right)-\omega^{ST_j}\cdot l\left(x,I_S^{ST_j*}\right)} > \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot l\left(x,I_S^{ST_i*}\right) > \omega^{ST_j} \cdot l\left(x,I_S^{ST_j*}\right)$

ii. If $\frac{\omega^{ST_i}-\omega^{ST_j}}{\omega^{ST_i}\cdot l\left(x,I_S^{ST_i*}\right)-\omega^{ST_j}\cdot l\left(x,I_S^{ST_j*}\right)} < \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot l\left(x,I_S^{ST_i*}\right) < \omega^{ST_j} \cdot l\left(x,I_S^{ST_j*}\right)$

c) When budget is sufficient for strategy i but not sufficient for strategy j,

i. If $\frac{c^{V_j}-c^{V_i}-c^{ST_i}}{\omega^{ST_i}\cdot f_S\left(I_S^{ST_i*}\right)-\omega^{ST_j}\cdot l\left(x,I_S^{ST_j*}\right)} > \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i*}\right) > \omega^{ST_j} \cdot l\left(x,I_S^{ST_j*}\right)$

ii. If $\frac{c^{V_j}-c^{V_i}-c^{ST_i}}{\omega^{ST_i}\cdot f_S\left(I_S^{ST_i*}\right)-\omega^{ST_j}\cdot l\left(x,I_S^{ST_j*}\right)} < \frac{\sigma_x}{\mu_x}$ when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i*}\right) < \omega^{ST_j} \cdot l\left(x,I_S^{ST_j*}\right)$

$$\text{where} \quad \omega^{ST_k} = r^G - c^{V_k} + c^{penalty}$$

Theorem 2 shows the contingency of the efficiency of the three risk mitigation strategies. The efficiency is highly affected not only by costs, prices, and budget but also by demand uncertainty. Figure E3-6 illustrates the performance of the three strategies under various demand uncertainty levels. In this figure, the profit curves for the *IIC* and *REC* strategies can take two shapes depending on the budget constraints. The gray lines that continue towards the upper left corner of the graph are for the case where budget B is sufficient. In that case, when demand uncertainty is low (Regions 1&2), *IIC* strategy dominates. *This is intuitive since a predictable and more profitable business warrants the* 3PL *investing in new capacity.* When demand uncertainty increases (Region 3), the *REC* strategy becomes the best option. This means, if there are transportation options at the right prices, using them as a risk mitigation strategy may make sense for the 3PL. We can also see that all the three strategies become irrelevant after a certain uncertainty threshold (Region 4). This means that the guaranteed capacity contract is not profitable for the 3PL beyond that threshold under any particular strategy.

When budget becomes restrictive for the *IIC* and *REC* strategies, the expected profit graphs for these two strategies become the black curves that have negative profits at low demand uncertainty. In this case, the *RIC* strategy is the best option in Region 1. *Since there is no upfront investment needed for RIC, it is the only strategy that can meet the shipper's demand at low uncertainty with insufficient investment budget B*. With increased demand uncertainty, the optimum capacity allocation levels decrease for all strategies (as illustrated in Figure E3-3), which make the budget problem for *IIC* and *REC* less significant. Thus, in Region 2, *REC* becomes the most profitable strategy. With further increase in demand uncertainty, in Region 3, *IIC* becomes the most profitable strategy.

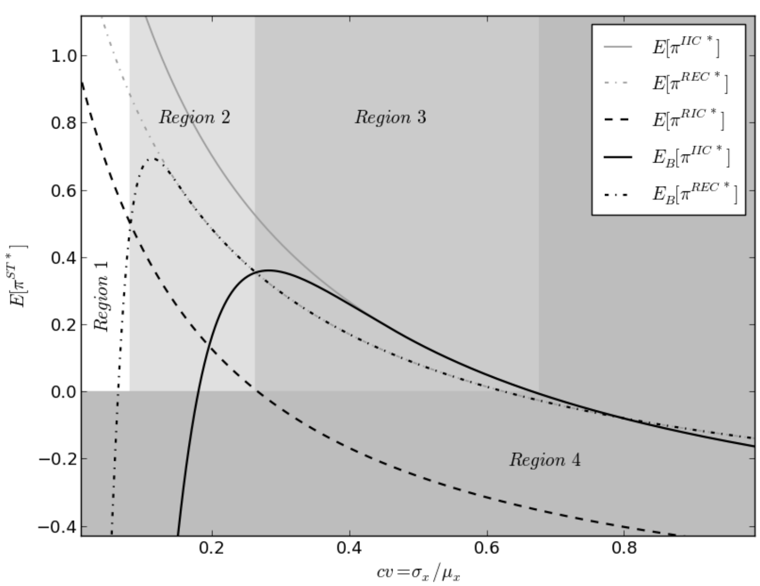

Figure E3-6: Strategy comparisons

In conducting the analysis in Figure E3-6, we made certain assumptions for the values of various parameters, which are based on industry averages and deduced from previous literature. To test the validity of our findings for other values of these parameters, we performed extensive sensitivity analysis, which is provided in Appendix B. The analysis shows that the overall findings are not impacted by the changes in parameter values, which ensures the robustness of the approach and the findings.

3.5. Using Multiple Strategies

In this section, we analyze the sequential use of multiple strategies. We first consider the case where the shipper has sufficient (unlimited) budget by extending our expected profit function for a single strategy to a mixed strategy that considers two different strategies sequentially. We define $ST_{i,j}$ as the mixed strategy composed of first using strategy i followed by strategy j. $I^{ST_{k(ij)}}$ represents the capacity allocation for strategy $k \in \{i,j\}$ under strategy $ST_{i,j}$. The expected profit of the 3PL in this case is composed of two parts: one from strategy i and the other from strategy j. The expected profit for the mixed strategy $ST_{i,j}$ is given by:

$$
\begin{aligned}
E\left[\pi^{ST_{i,j}}\right] = {} & -c^{ST_i} I^{ST_{i(ij)}} - c^{ST_j} I^{ST_{j(ij)}} + (r^G - c^{V_i}) \int_0^{\infty} \min\left(x, I^{ST_{i(ij)}}\right) dF(x) \\
& + \left(r^G - c^{V_j}\right) \int_{I^{ST_{i(ij)}}}^{\infty} \min\left(x - I^{ST_{i(ij)}}, I^{ST_{j(ij)}}\right) dF(x) \\
& - c^{penalty} \int_{I^{ST_{i(ij)}} + I^{ST_{j(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}} - I^{ST_{j(ij)}}\right) dF(x)
\end{aligned}
$$

The following theorem identifies the shipper's optimal decision for capacity allocations when strategies i and j are both used.

Theorem 3. Mixed strategy $ST_{i,j}$ is better than the sole strategies ST_i and ST_j if all of the following conditions are satisfied: i) $c^{V_i} < c^{V_j}$, ii) $1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}} > F_S\left(-\frac{\mu_x}{\sigma_x}\right)$ and iii) $\frac{c^{ST_i}}{c^{ST_j}} > \frac{r^G - c^{V_i} + c^{penalty}}{r^G - c^{V_j} + c^{penalty}}$. Moreover, the optimal capacity allocation levels for strategy i followed by strategy j under unlimited budget are given by:

$$I^{ST_{i(ij)}}{}^* = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}\right) + \mu_x \text{ and}$$

$$I^{ST_{j(ij)}}{}^* = \sigma_x \left[F_S^{-1}\left(1 - \frac{c^{ST_j}}{r^G - c^{V_j} + c^{penalty}}\right) - F_S^{-1}\left(1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}\right)\right]$$

, respectively.

Proof is provided in Appendix A.

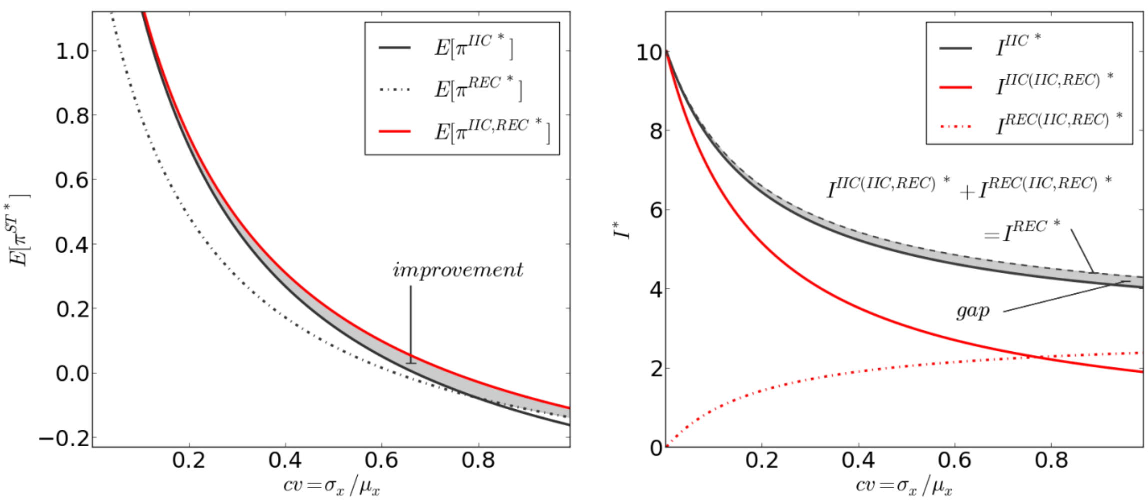

Figure E3-7: Mixed strategy with *IIC* and *REC* under unlimited budget

To illustrate the performance of a mixed strategy, in comparison to sole strategies, we use the mixed strategy $(ST_{IIC,REC})$ as an example since the cost data used for *IIC* and *REC* strategies satisfies the three conditions of Theorem 3. The graph on the left side of Figure E3-7 illustrates the expected profit of the mixed strategy compared to the sole strategies as the demand variability changes. Similarly, the graph on the right illustrates the capacity allocation levels for the mixed and sole strategies. By Theorem 3, at the starting point of the mixed strategy (i.e., when $\sigma_x = 0$), the optimal capacity allocation level for the first used strategy equals to μ_x, which is equals to 10, and the capacity allocation level for the second used strategy is equal to zero. However, as the demand variability increases, the amount of capacity allocated for the first used strategy $\left(I^{IIC\,(IIC,REC)^*}\right)$ begins to decrease and the amount of capacity allocated for the second used strategy $\left(I^{REC\,(IIC,REC)^*}\right)$ begins to increase. Interestingly, the summation of these two amounts is always equal to the optimal capacity allocation level $\left(I^{REC^*}\right)$ in sole strategy *REC*.

In the expected profit graph on the left in Figure E3-7, we see that the expected profit curve of the mixed strategy begins to dominate the expected profit curves of both of the sole strategies (*IIC* and *REC*), thus providing a higher expected profit for all levels of demand variability. This case clearly shows that a mixed strategy may provide better profits than sole strategies under certain cost conditions when there is no budget constraint. One interpretation of the expected profit curves in Figure E3-7 can be as follows: in the mixed strategy, the first used strategy dictates the starting point of the mixed strategy's expected profit curve, while the second used strategy dictates the shape of the curve. Therefore, in the case of the mixed strategy with *IIC* and *REC*, first using *IIC* allows beginning at a good starting point and then using *REC* allows reducing the speed of profit decrease as demand variability increases.

For the case of limited budget (subscript B denotes budget B), we consider the possibility of using *RIC* strategy as a secondary strategy within a mixed strategy (*IIC*, *RIC*). When the primary strategy (*IIC*) is constrained by the budget limit in the mixed strategy, *RIC* may be utilized since the fixed cost of *RIC* is only an opportunity cost by definition and not constrained by the fixed budget.

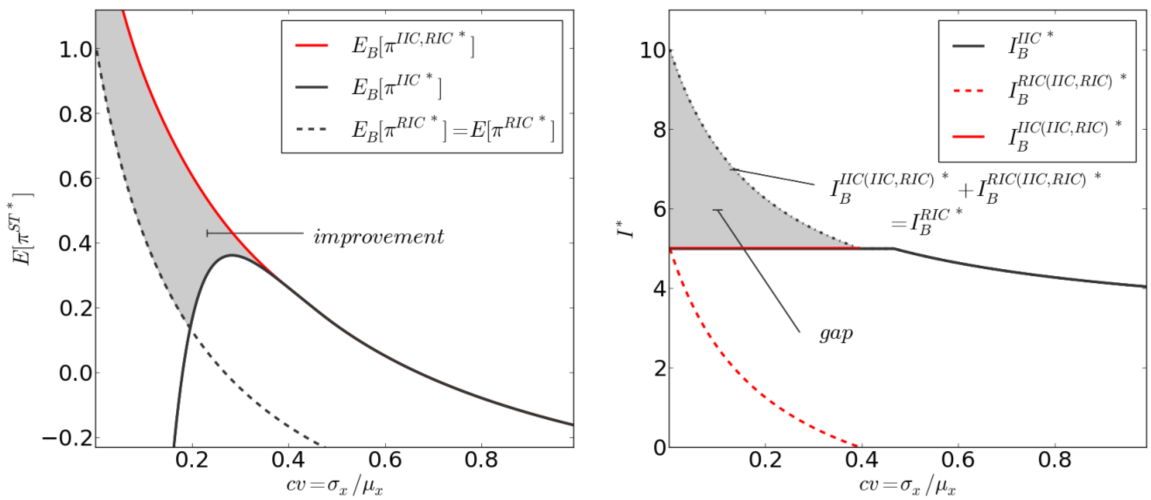

Figure E3-8: Mixed strategy with *IIC* and *RIC* under limited budget

In the expected profit graph on the left in Figure E3-8, the mixed strategy's expected profit curve $\left(E_B\left[\pi^{IIC,RIC^*}\right]\right)$ dominates the expected profit of the sole strategies $\left(E_B\left[\pi^{IIC^*}\right], E_B\left[\pi^{RIC^*}\right]\right)$ until demand variability reaches a threshold value of cv~0.35. After this value, the mixed strategy and the *IIC* sole strategy produce the same level of expected profit. This case clearly shows that a mixed strategy may provide better profits than sole strategies under certain cost and demand conditions when there is a limited budget for the upfront investments. In the graph on the right of Figure E3-8, we see that the optimal capacity allocation level $({I_B}^{IIC^*})$ is restricted by the limited budget for a range of demand variability. Within this range, the amount of capacity allocated for the secondary strategy $\left({I_B}^{RIC(IIC,RIC)^*}\right)$ begins at a high level and gradually decreases and becomes zero. Similar to the observation made for the unlimited budget case in Figure E3-7, we again observe here that the summation of the capacity allocation for the primary strategy

$\left(I_B^{IIC(IIC,RIC)^*}\right)$ and the secondary strategy $\left(I_B^{RIC(IIC,RIC)^*}\right)$ is always equal to the optimal capacity allocation level $(I_B^{RIC^*})$ in sole strategy *RIC*.

4. Managerial Implications

Transportation is an important activity in a relationship between a buyer and a seller, especially if they are significantly distant from each other. A guaranteed transportation capacity would be very helpful in maintaining a healthy relationship between the buyer and the supplier. The challenge is how would the transportation service stay profitable and yet the guaranteed capacity can be provided. Many economic indicators such as Purchasing Managers' Indexes (PMI) are showing signs of a surge of new freight[15]. However, the carriers hesitate to expand their capacity because of the cost of new equipment[16]. Our analysis can assist the 3PLs as well as firms with private fleets who are considering capacity expansion, but constrained with budget issues, to make reliable decisions. For example, if we assume that the standard revenue for a truckload service is \$1000 for a given lane and if we assume a relatively predictable demand (when $cv = 0.21$), investing in additional capacity (*IIC*) can result in an increase in expected profit of \$230.28, which is higher than the expected profit of \$104.57 that would be earned without capacity expansion (*RIC*). With this type of analysis performed, the first insight that we provide is that with the right set of cost, price and demand parameters, guaranteed capacity contracts may be a viable option. This can help appease some of the capacity crunch that a shipper is currently facing.

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[15] http://www.industryweek.com/global-economy/manufacturing-expands-february-ism-reports

[16] http://www.joc.com/trucking-logistics/truckload-freight/truckload-capacity-rises-remains-near-historic-low_20140814.html

The second main insight is regarding the demand uncertainty. Our analysis shows that, as demand uncertainty increases, the profitability of guaranteed capacity arrangement decreases rapidly for the 3PL. Although demand certainty is not required and perhaps not feasible in many instances, low to medium demand uncertainty is very desirable from the 3PL's perspective in planning capacity options. Our analysis clearly demonstrates that within this range 3PLs can operate in an effective manner that would be profitable for both the buyer and the supplier.

As a third insight, we demonstrate that, depending on the budget constraints of the 3PL, choosing a mitigation strategy that provides the highest profit can be characterized based on the demand characterizations and cost parameters. As discussed in our results, under conditions of risk and uncertainty, there is no one-size-fits all type of a strategy. The response of the 3PLs is contingent on the environment that they are subjected to.

As a fourth insight, we demonstrate that mixed use of strategies can produce higher expected profits under certain demand and cost parameter settings, which are explicitly characterized for the unlimited budget case. For the limited budget case, we also provide a sample case on how a mixed strategy can be very useful even with a restriction on the upfront investment.

From an application standpoint of the methods developed in this paper, while we understand that such an analysis and related technical expertise is often not readily available in the industry, it certainly helps decision-makers in developing a decision support system (DSS) that can be applied in a variety of settings. Given the availability of a number of advanced planning and scheduling (APS) systems with decision making capabilities, our approach and models can fit into such an environment where the user does not really need to develop these capabilities from scratch but can readily utilize them in making effective decisions.

5. Conclusions and Extensions

Transportation is an essential logistical activity that bridges the geographic gap between a buyer and a seller. Without effective and efficient transportation service, it is not possible to achieve complete supply chain integration. Transportation capacity shortage has been an important issue for the shippers for the past few years. Inability to access affordable transportation capacity in a timely manner can result in increased costs and reduced level of on-time deliveries, which in turn can create serious problems between buyers and sellers of products and services. This issue becomes relevant for firms that focus on lean operations by eliminating inventory in their system and by adopting just-in-time manufacturing. Similarly, as the US economy continues its transformation towards service, more service oriented firms are also facing a similar issue as these firms cannot tolerate any delay in transportation, which can cause problems for buyers that rely on timely deliveries. In this context, this study evaluates the behavior of three alternative risk mitigation strategies and the mixed use of these strategies that can be utilized by a 3PL or a shipper with a private fleet, which faces a capacity management decision, by considering a variety of factors such as budget, cost, price, and demand. We demonstrated that the effectiveness of these alternative risk mitigation strategies is contingent on a variety of settings and show that there is no one strategy that is considered superior to others under all conditions.

While research in risk management has extensively focused on manufacturing processes, the consideration of risk aspects in transportation and logistics operations is relatively sparse. To this end, our paper is first of its kind that has effectively demonstrated the treatment of risk aspects in a transportation setting under the broad rubric of buyer-supplier relationships. We expect that our work will act as a catalyst in further investigating this important research domain that has been receiving significant exposure in practitioner circles.

Although this paper focuses on trucking, the analysis can be extended to other forms of transportation (air, rail, intermodal, etc.). However, the practical applicability of the analysis would be most appropriate to trucking since the capacity of other modes is very high compared to trucking and requires a large enough customer base to generate a significant demand increase for the carrier to justify considering capacity decisions.

Finally, our approach is not devoid of limitations. There are several possible extensions for this study. First, while we have made an effort to anchor the problem in practice through two case examples and relevant data from industry, a more detailed implementation of our framework would add significant value. Second, our paper considers a single period problem, which does not seem appropriate at first for capacity related decisions since such decisions involve high upfront fixed costs and relatively low but recurring variable costs during the lifetime of the assets. However, notice that all the costs, including fixed costs, used in this paper are per mile average industry-level costs, and not total actual costs spent. Thus, by making the analysis on per-mile costs, our results based on single period analyses implicitly takes into account the multi-period repetitive nature of the problem, since these averages are calculated based on the lifetime costs of transportation equipment. However, we also recognize that a more comprehensive scenario would be to consider the arrival of multiple customers at multiple future periods that would require an explicit multi-period capacity management analysis using actual cost figures. Similar to the evolution of inventory models, going from single-period to multiple-period, we conduct our analysis on a single period while deferring the explicit multi-period analysis to a future study. Finally, the underlying reasons for guaranteed demand (cyclical weather patterns, economic conditions, etc.) are not explicitly handled in our models, which is a possible extension that can be handled by a simulation study.

APPENDICES

Appendix A: Poof of Proposition 1

Proof 1. Given the variable x with mean μ_x, standard deviation σ_x, and cumulative distribution $F(x)$, we define the standardized variable z to be $z = \frac{x-\mu_x}{\sigma_x}$. z has the cumulative distribution $F_S(z)$ with mean 0 and standard deviation 1. Given a value R of x, we define $R_S = \frac{R-\mu_x}{\sigma_x}$. The standardized loss function is defined as

$$l(x,R_S) = \int_{R_S}^{\infty} \left(1 - F_S(z)\right) dz$$

The expected profit function can be modified as follows.

$$E[\pi^{ST_k}] = -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^{\infty} \min(x, I^{ST_k})\, dF(x)$$

$$- c^{penalty} \int_{I^{ST_k}}^{\infty} (x - I^{ST_k})\, dF(x)$$

$$= -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^{I^{ST_k}} x\, dF(x) + (r^G - c^{V_k}) \int_{I^{ST_k}}^{\infty} I^{ST_k}\, dF(x)$$

$$- c^{penalty} \int_{I^{ST_k}}^{\infty} (x - I^{ST_k})\, dF(x)$$

$$= -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^{I^{ST_k}} x\, dF(x) + \left(r^G - c^{V_k} + c^{penalty}\right) \int_{I^{ST_k}}^{\infty} I^{ST_k}\, dF(x)$$

$$- c^{penalty} \int_{I^{ST_k}}^{\infty} x\, dF(x)$$

$$= -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^{\infty} x\, dF(x) - (r^G - c^{V_k}) \int_{I^{ST_k}}^{\infty} x\, dF(x)$$

$$+ \left(r^G - c^{V_k} + c^{penalty}\right) \int_{I^{ST_k}}^{\infty} I^{ST_k}\, dF(x) - c^{penalty} \int_{I^{ST_k}}^{\infty} x\, dF(x)$$

$$= -c^{ST_k} I^{ST_k} + (r^G - c^{V_k}) \int_0^{\infty} x\, dF(x) - \left(r^G - c^{V_k} + c^{penalty}\right) \int_{I^{ST_k}}^{\infty} (x - I^{ST_k})\, dF(x)$$

$$= -c^{ST_k} I^{ST_k} + (r^G - c^{V_k})\mu_x - \left(r^G - c^{V_k} + c^{penalty}\right) \int_{I^{ST_k}}^{\infty} (x - I^{ST_k})\, dF(x)$$

Observe that

$$\int_{I^{ST_k}}^{\infty} (x - I^{ST_k})\, dF(x) = \int_{I_S^{ST_k}}^{\infty} (x - I^{ST_k}) dF_S(z) = \int_{I_S^{ST_k}}^{\infty} (\sigma_x z + \mu_x - I^{ST_k}) dF_S(z)$$

$$= \int_{I_S^{ST_k}}^{\infty} \left(\sigma_x z + \mu_x - \left(\sigma_x I_S^{ST_k} + \mu_x\right)\right) dF_S(z) = \int_{I_S^{ST_k}}^{\infty} \sigma_x \left(z - I_S^{ST_k}\right) dF_S(z)$$

$$= \sigma_x \int_{I_S^{ST_k}}^{\infty} \left(z - I_S^{ST_k}\right) dF_S(z) = \sigma_x \int_{I_S^{ST_k}}^{\infty} \left(1 - F_S(z)\right) dz = \sigma_x l\left(x, I_S^{ST_k}\right)$$

So,

$$E[\pi^{ST_k}] = -c^{ST_k} I^{ST_k} + (r^G - c^{V_k})\mu_x - \left(r^G - c^{V_k} + c^{penalty}\right)\sigma_x l\left(x, I_S^{ST_k}\right)$$

The standardized loss function $l\left(x, I_S^{ST_k}\right) = \int_{I_S^{ST_k}}^{\infty} \left(1 - F_S(z)\right) dz$, where $I_S^{ST_k} = \frac{I^{ST_k} - \mu_x}{\sigma_x}$.

Observe that

$$\frac{\partial}{\partial I^{ST_k}} l\left(x, I_S^{ST_k}\right) = -\frac{1}{\sigma_x}\left(1 - F_S\left(\frac{I^{ST_k} - \mu_x}{\sigma_x}\right)\right)$$

$$\frac{\partial^2}{\partial (I^{ST_k})^2} l\left(x, I_S^{ST_k}\right) = \frac{1}{\sigma_x^2} f_S\left(\frac{I^{ST_k} - \mu_x}{\sigma_x}\right) \geq 0$$

, which means the standardized loss function is convex.

Observe that

$$\frac{\partial}{\partial I^{ST_k}} E[\pi^{ST_k}] = -c^{ST_k} - \left(r^G - c^{V_k} + c^{penalty}\right)\sigma_x \frac{\partial}{\partial I^{ST_k}} l\left(x, I_S^{ST_k}\right)$$

$$\frac{\partial^2}{\partial (I^{ST_k})^2} E[\pi^{ST_k}] = -\left(r^G - c^{V_k} + c^{penalty}\right)\sigma_x \frac{\partial^2}{\partial (I^{ST_k})^2} l\left(x, I_S^{ST_k}\right)$$

implying that if $r^G - c^{V_k} + c^{penalty} > 0$, $E[\pi^{ST_k}]$ is concave. But, by assumption that variable cost is always lower than revenue, $r^G - c^{V_k} + c^{penalty}$ cannot be negative so that

$E[\pi^{ST_k}]$ cannot be convex. Thus, $I^{ST_k *}$ is obtained by setting $\frac{\partial}{\partial I^{ST_k}} E[\pi^{ST_k}] = 0$, which gives

$$I^{ST_k} = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x$$

Since $I^{ST_k} \geq 0$, we obtain

$$I^{ST_k} = \max\left(0, \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x\right)$$

If $c^{ST_k} I^{ST_k}$ is greater than B, $I^{ST_k} = B(y_k c^{ST_k})^{-1}$, since $E[\pi^{ST_k}]$ is concave in I^{ST_k}, i.e., $E[\pi^{ST_k}]$ is increasing in I^{ST_k} when $0 \leq I^{ST_k} \leq \max\left(0, \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x\right)$.

Therefore, $I^{ST_k *} = \max\left(0, \min\left(B(y_k c^{ST_k})^{-1}, \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x\right)\right)$. ■

Appendix B: Proof of Theorem 1

Proof 2. The loss function can be expressed as follows

$$l(x,R_S) = \int_{R_S}^{\infty}\big(1 - F_S(z)\big)dz = \int_{R_S}^{\infty}(z - R_S)dF_S(z) = \int_{V_S}^{\infty}(z - R_S)f_S(z)dz$$

$$= \int_{R_S}^{\infty} z f_S(z)dz - R_S\big(1 - F_S(R_S)\big) = \left[-\frac{e^{-\frac{1}{2}z^2}}{\sqrt{2\pi}}\right]_{R_S}^{\infty} - R_S\big(1 - F_S(R_S)\big)$$

$$= 0 + \frac{e^{-\frac{1}{2}R_S^2}}{\sqrt{2\pi}} - R_S\big(1 - F_S(R_S)\big) = f_S(R_S) - R_S\big(1 - F_S(R_S)\big)$$

When $I^{ST_k *} = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) + \mu_x$, by substituting this revised form of loss function and $I^{ST_k *}$ into $E[\pi^{ST_k}]$, we can derive optimal expected profit function as following.

$$E\left[\pi^{ST_k *}\right] = -\sigma_x\left(c^{ST_k}F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right)\right) + (r^G - c^{V_k} - c^{ST_k})\mu_x$$

$$- \sigma_x\left(r^G - c^{V_k} + c^{penalty}\right)\left(f_S\left(F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right)\right)\right.$$

$$\left. - F_S^{-1}\left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right)\left(\frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right)\right)$$

Now, let $\omega^{ST_k} = r^G - c^{V_k} + c^{penalty}$. Then, by simple algebra, we have

$$E\left[\pi^{ST_k *}\right] = (r^G - c^{V_k} - c^{ST_k})\mu_x - \sigma_x\omega^{ST_k}\left(f_S\left(F_S^{-1}\left(1 - \frac{c^{ST_k}}{\omega^{ST_k}}\right)\right)\right)$$

Observe that $F_S^{-1}\left(1 - \frac{c^{ST_k}}{\omega^{ST_k}}\right) = I_S^{ST_k *}$. So, by substituting the observation and simple algebra, we can conclude that when $\frac{r^G - c^{V_k} - c^{ST_k}}{\omega^{ST_k}\left(f_S\left(I_S^{ST_k *}\right)\right)} \geq \frac{\sigma_x}{\mu_x}$, strategy k will give better profit, since $\omega^{ST_k} > 0$ (by assumption) and $f_S\left(I_S^{ST_k{}^*}\right) > 0$ ($f_S(\cdot)$ is p.d.f. of standard normal). Similarly, when $I^{ST_k{}^*} = \frac{B}{y_k c^{ST_k}}$, $E\left[\pi^{ST_k{}^*}\right] = (r^G - c^{V_k})\mu_x - \omega^{ST_k}\sigma_x l\left(x, I_S^{ST_k{}^*}\right)$. This implies that if $\frac{r^G - c^{V_k}}{\omega^{ST_k}\sigma_x l\left(x, I_S^{ST_k{}^*}\right)} \geq \frac{\sigma_x}{\mu_x}$, strategy k will give better profit.■

Appendix C: Proof of Proposition 2

Proof 3. When budget constraint is activated, ${I^{ST_k}}^* = B(y_k c^{ST_k})^{-1}$. Then, $\frac{\partial}{\partial c^{ST_k}} {I^{ST_k}}^* = -B(y_k c^{ST_k})^{-2} < 0$. But, when budget constraint is not activated and ${I^{ST_k}}^* > 0$,

$$\frac{\partial}{\partial c^{ST_k}} {I^{ST_k}}^* = -\frac{\sigma_x}{r^G - c^{V_k} + c^{penalty}} {F_S^{-1}}' \left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) \leq 0$$

$$\text{and } \frac{\partial}{\partial c^{V_k}} {I^{ST_k}}^* = -\frac{\sigma_x c^{ST_k}}{(r^G - c^{V_k} + c^{penalty})^2} {F_S^{-1}}' \left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) \leq 0$$

, since ${F_S^{-1}}'(\cdot)$, i.e., first derivative of inverse standard normal c.d.f., is non-negative and $\frac{\sigma_x}{r^G - c^{V_k} + c^{penalty}} \geq 0$. This implies that ${I^{ST_k}}^*$ is decreasing in c^{ST_k} and c^{V_k}. Moreover, if $\frac{\partial}{\partial c^{ST_k}} {I^{ST_k}}^* < \frac{\partial}{\partial c^{V_k}} {I^{ST_k}}^*$, the negative impact of c^{ST_k} is greater than c^{V_k}. But, $-\frac{\sigma_x}{r^G - c^{V_k} + c^{penalty}} {F_S^{-1}}' \left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) <$
$-\frac{\sigma_x c^{ST_k}}{(r^G - c^{V_k} + c^{penalty})^2} {F_S^{-1}}' \left(1 - \frac{c^{ST_k}}{r^G - c^{V_k} + c^{penalty}}\right) \Leftrightarrow r^G - c^{V_k} + c^{penalty} > c^{ST_k}$, which is always true by definition. Therefore, the argument holds. ■

Appendix D: Proof of Theorem 2

Proof 4. From the proof of Theorem 1,

$$E\left[\pi^{ST_i{}^*}\right] = (r^G - c^{V_i} - c^{ST_i})\mu_x - \sigma_x \omega^{ST_i}\left(f_S\left(I_S^{ST_i{}^*}\right)\right)$$

Similarly,

$$E\left[\pi^{ST_j{}^*}\right] = \left(r^G - c^{V_j} - c^{ST_j}\right)\mu_x - \sigma_x \omega^{ST_j}\left(f_S\left(I_S^{ST_j{}^*}\right)\right)$$

So, $E\left[\pi^{ST_i{}^*}\right] - E\left[\pi^{ST_j{}^*}\right] = \left(\omega^{ST_i} - \omega^{ST_j} + c^{ST_j} - c^{ST_i}\right)\mu_x - \sigma_x\left[\omega^{ST_i} \cdot f_S\left(I_S^{ST_i{}^*}\right) - \omega^{ST_j} \cdot f_S\left(I_S^{ST_j{}^*}\right)\right]$. This implies that if it is greater than zero, ST_i is better than ST_j. Thus, when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i{}^*}\right) > \omega^{ST_j} \cdot f_S\left(I_S^{ST_j{}^*}\right)$, ST_i is better if $\frac{\omega^{ST_i} - \omega^{ST_j} + c^{ST_j} - c^{ST_i}}{\omega^{ST_i} \cdot f_S\left(I_S^{ST_i{}^*}\right) - \omega^{ST_j} \cdot f_S\left(I_S^{ST_j{}^*}\right)} > \frac{\sigma_x}{\mu_x}$ but when $\omega^{ST_i} \cdot f_S\left(I_S^{ST_i{}^*}\right) < \omega^{ST_j} \cdot f_S\left(I_S^{ST_j{}^*}\right)$, ST_i is better if $\frac{\omega^{ST_i} - \omega^{ST_j} + c^{ST_j} - c^{ST_i}}{\omega^{ST_i} \cdot f_S\left(I_S^{ST_i{}^*}\right) - \omega^{ST_j} \cdot f_S\left(I_S^{ST_j{}^*}\right)} < \frac{\sigma_x}{\mu_x}$.

When budget constraint is activated $I^{ST_k{}^*} = Bc^{ST_k{}^{-1}}$. By substituting this optimal value into expected profit function, we can similarly derive the determinants for part b and c. ■

Appendix E: Proof of Theorem 3

Proof 5. $\pi^{ST_{i,j}}$ denotes the profit of a mixed strategy that uses strategy i first and then strategy j.

$$E\left[\pi^{ST_{i,j}}\right] = -c^{ST_i} I^{ST_{i(ij)}} - c^{ST_j} I^{ST_{j(ij)}} + (r^G - c^{V_i}) \int_0^{\infty} \min\left(x, I^{ST_{i(ij)}}\right) dF(x)$$

$$+ \left(r^G - c^{V_j}\right) \int_{I^{ST_{i(ij)}}}^{\infty} \min\left(x - I^{ST_{i(ij)}}, I^{ST_{j(ij)}}\right) dF(x)$$

$$- c^{penalty} \int_{I^{ST_{i(ij)}} + I^{ST_{j(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}} - I^{ST_{j(ij)}}\right) dF(x)$$

$$= -c^{ST_i} I^{ST_{i(ij)}} - c^{ST_j} I^{ST_{j(ij)}} + (r^G - c^{V_i}) \int_0^{\infty} x \, dF(x)$$

$$+ \left(c^{V_i} - c^{V_j}\right) \int_{I^{ST_{i(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}}\right) dF(x)$$

$$- \left(r^G - c^{V_j} + c^{penalty}\right) \int_{I^{ST_{i(ij)}} + I^{ST_{j(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}} - I^{ST_{j(ij)}}\right) dF(x)$$

$$= -c^{ST_i} I^{ST_{i(ij)}} - c^{ST_j} I^{ST_{j(ij)}} + (r^G - c^{V_i}) \mu_x + \left(c^{V_i} - c^{V_j}\right) \int_{I^{ST_{i(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}}\right) dF(x)$$

$$- \left(r^G - c^{V_j} + c^{penalty}\right) \int_{I^{ST_{i(ij)}} + I^{ST_{j(ij)}}}^{\infty} \left(x - \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)\right) dF(x)$$

Note that if $I^{ST_{j(ij)}} = 0$ ($I^{ST_{i(ij)}} = 0$), it can be shown that $E\left[\pi^{ST_{i,j}}\right] = E\left[\pi^{ST_i}\right]$ ($E\left[\pi^{ST_{i,j}}\right] = E\left[\pi^{ST_j}\right]$) by simple algebra. As observed before in proposition 1, we again observe that $\int_{I^{ST_{i(ij)}}}^{\infty} \left(x - I^{ST_{i(ij)}}\right) dF(x) = \sigma_x l\left(x, I_S^{ST_{i(ij)}}\right)$ and similarly, $\int_{I^{ST_{i(ij)}} + I^{ST_{j(ij)}}}^{\infty} \left(x - \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)\right) dF(x) = \sigma_x l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right)$. So, we can simplify the expected profit of $ST_{i,j}$ as follows:

$$E\left[\pi^{ST_{i,j}}\right] = -c^{ST_i} I^{ST_{i(ij)}} - c^{ST_j} I^{ST_{j(ij)}} + (r^G - c^{V_i})\mu_x + \left(c^{V_i} - c^{V_j}\right)\sigma_x l\left(x, I_S^{ST_{i(ij)}}\right)$$

$$- \left(r^G - c^{V_j} + c^{penalty}\right)\sigma_x l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right)$$

Observe that

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, I_S^{ST_{i(ij)}}\right) = -\frac{1}{\sigma_x}\left(1 - F_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right)\right)$$

$$\frac{\partial^2}{\partial {I^{ST_{i(ij)}}}^2} l\left(x, I_S^{ST_{i(ij)}}\right) = \frac{1}{\sigma_x^2} f_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right) \geq 0 \qquad \text{A(1)}$$

, which means the standardized loss function is convex. Similarly,

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right) = \frac{\partial}{\partial I^{ST_{j(ij)}}} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right)$$

$$= -\frac{1}{\sigma_x}\left(1 - F_S\left(\frac{\left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right) - \mu_x}{\sigma_x}\right)\right) \qquad \text{A(2)}$$

$$\frac{\partial^2}{\partial {I^{ST_{i(ij)}}}^2} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right) = \frac{\partial^2}{\partial {I^{ST_{j(ij)}}}^2} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right)$$

$$= \frac{1}{\sigma_x^2} f_S\left(\frac{\left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right) - \mu_x}{\sigma_x}\right) \geq 0 \qquad \text{A(3)}$$

But, observe that

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right]$$

$$= -c^{ST_i} + \left(c^{V_i} - c^{V_j}\right)\sigma_x \frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, I_S^{ST_{i(ij)}}\right) \qquad \text{A(4)}$$

$$- \left(r^G - c^{V_j} + c^{penalty}\right)\sigma_x \frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right) \text{ and}$$

$$\frac{\partial}{\partial I^{ST_{j(ij)}}} E\left[\pi^{ST_{i,j}}\right]$$

$$= -c^{ST_j} \qquad \text{A(5)}$$

$$-\left(r^G - c^{V_j} + c^{penalty}\right)\sigma_x \frac{\partial}{\partial I^{ST_{j(ij)}}} l\left(x, \left(I^{ST_{i(ij)}} + I^{ST_{j(ij)}}\right)_S\right)$$

Thus, by using A(2) and A(5), we rearrange Eq. A(4) as follows:

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] = -c^{ST_i} + \left(c^{V_i} - c^{V_j}\right)\sigma_x \frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, I_S^{ST_{i(ij)}}\right) + \frac{\partial}{\partial I^{ST_{j(ij)}}} E\left[\pi^{ST_{i,j}}\right] + c^{ST_j}$$

Since the expected profit is concave w.r.t. $I^{ST_{j(ij)}}$ by Eq. A(3) and the fact that unit revenue for the guaranteed capacity service is always assumed to be higher than unit variable cost under strategy j, i.e., $r^G > c^{V_j}$, then $\frac{\partial}{\partial I^{ST_{j(ij)}}} E\left[\pi^{ST_{i,j}}\right] = 0$ at optimality. Using these observations, we obtain

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] = -c^{ST_i} + \left(c^{V_i} - c^{V_j}\right)\sigma_x \frac{\partial}{\partial I^{ST_{i(ij)}}} l\left(x, I_S^{ST_{i(ij)}}\right) + c^{ST_j}$$

$$= c^{ST_j} - c^{ST_i} - \left(c^{V_i} - c^{V_j}\right)\left(1 - F_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right)\right) \text{ and}$$

$$\frac{\partial^2}{\partial {I^{ST_{i(ij)}}}^2} E\left[\pi^{ST_{i,j}}\right] = \left(c^{V_i} - c^{V_j}\right)\sigma_x \frac{\partial^2}{\partial {I^{ST_{i(ij)}}}^2} l\left(x, I_S^{ST_{i(ij)}}\right)$$

, which means that $E\left[\pi^{ST_{i,j}}\right]$ can be either i) concave or ii) convex w.r.t. $I^{ST_{i(ij)}}$

i) If $c^{V_i} - c^{V_j} < 0$, $E\left[\pi^{ST_{i,j}}\right]$ is concave w.r.t. $I^{ST_{i(ij)}}$ by Eq. A(1).

So, when $c^{V_i} - c^{V_j} < 0$, setting $\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] = 0$ gives

$$F_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right) = 1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}$$

Solving for $I^{ST_{i(ij)}}$ gives optimal capacity allocation for guaranteed capacity service of strategy i in $ST_{i,j}$.

$$I^{ST_{i(ij)}}{}^{*} = \max\left(0, \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}\right) + \mu_x\right)$$

$I^{ST_{j(ij)}}{}^{*}$ is obtained by setting $\frac{\partial}{\partial I^{ST_{j(ij)}}} E\left[\pi^{ST_{i,j}}\right] = 0$ with $I^{ST_{i(ij)}} = I^{ST_{i(ij)}}{}^{*}$, which gives

$$-c^{ST_j} + \left(r^G - c^{V_j} + c^{penalty}\right)\left(1 - F_S\left(\frac{\left(I^{ST_{i(ij)}}{}^{*} + I^{ST_{j(ij)}}\right) - \mu_x}{\sigma_x}\right)\right) = 0$$

By solving this for $I^{ST_{j(ij)}}$, we obtain

$$I^{ST_{j(ij)}}{}^{*} = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j}}{r^G - c^{V_j} + c^{penalty}}\right) + \mu_x - I^{ST_{i(ij)}}{}^{*} \qquad \text{A(6)}$$

ii) On the other hand, if $c^{V_i} - c^{V_j} \geq 0$, $E\left[\pi^{ST_{i,j}}\right]$ is convex w.r.t. $I^{ST_{i(ij)}}$ by Eq. A(1).

When $\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] < 0$, i.e.,

$$\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] = c^{ST_j} - c^{ST_i} - \left(c^{V_i} - c^{V_j}\right)\left(1 - F_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right)\right) < 0$$

$$\Leftrightarrow \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}} < 1 - F_S\left(\frac{I^{ST_{i(ij)}} - \mu_x}{\sigma_x}\right) \Leftrightarrow I^{ST_{i(ij)}}$$

$$< \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}\right) + \mu_x$$

, the minimum value for $I^{ST_{i(ij)}}$ is the best, i.e., $I^{ST_{i(ij)}} = 0$ (lower bound) so that $I^{ST_{j(ij)}} = \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j}}{r^G - c^{V_j} + c^{penalty}}\right) + \mu_x = I^{ST_j}{}^{*}$. Thus, the mixed strategy is the same as the sole strategy j and does not generate a better expected profit. Similarly, when $\frac{\partial}{\partial I^{ST_{i(ij)}}} E\left[\pi^{ST_{i,j}}\right] \geq 0$, i.e., $I^{ST_{i(ij)}} > \sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j} - c^{ST_i}}{c^{V_i} - c^{V_j}}\right) + \mu_x$. The maximum $I^{ST_{i(ij)}}$ is the best, which implies that $I^{ST_{i(ij)}}{}^{*}$ can be increased up to $\sigma_x F_S^{-1}\left(1 - \frac{c^{ST_j}}{r^G - c^{V_j} + c^{penalty}}\right) + \mu_x$ (upper bound). Thus,

$$\sigma_x F_S^{-1}\left(1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}\right)+\mu_x<\sigma_x F_S^{-1}\left(1-\frac{c^{ST_j}}{r^G-c^{V_j}+c^{penalty}}\right)+\mu_x$$

$$\Leftrightarrow \frac{c^{ST_i}}{c^{ST_j}}<\frac{r^G-c^{V_i}+c^{penalty}}{r^G-c^{V_j}+c^{penalty}}<1 \qquad \text{A(7)}$$

At the upper bound, $I^{ST_{i(ij)}}=\sigma_x F_S^{-1}\left(1-\frac{c^{ST_j}}{r^G-c^{V_j}+c^{penalty}}\right)+\mu_x$ and $I^{ST_{j(ij)}}=0$ due to A(6). If $I^{ST_{i(ij)}}>I^{ST_i}$, $\pi^{ST_{i,j}}$ can be greater than π^{ST_i}. However, $I^{ST_{i(ij)}}>I^{ST_i} \Leftrightarrow \frac{c^{ST_i}}{c^{ST_j}}>\frac{r^G-c^{V_i}+c^{penalty}}{r^G-c^{V_j}+c^{penalty}}$, which contradicts Eq. A(7). This implies that $ST_{i,j}$ is not better than sole strategy ST_i in this case either.

Therefore, under unlimited budget, combination of i and j can be a viable option for the mixed strategy only when $c^{V_i}-c^{V_j}<0$ and when $I^{ST_{i(ij)}}{}^*$ and $I^{ST_{j(ij)}}{}^*$ are both positive, i.e., $\sigma_x F_S^{-1}\left(1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}\right)+\mu_x>0 \Leftrightarrow 1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}>F_S\left(-\frac{\mu_x}{\sigma_x}\right)$ and $\sigma_x\left[F_S^{-1}\left(1-\frac{c^{ST_j}}{r^G-c^{V_j}+c^{penalty}}\right)-F_S^{-1}\left(1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}\right)\right]>0 \Leftrightarrow \frac{c^{ST_i}}{c^{ST_j}}>\frac{r^G-c^{V_i}+c^{penalty}}{r^G-c^{V_j}+c^{penalty}}$. Therefore, when these conditions are satisfied, the optimal solution is given by

$$I^{ST_{i(ij)}}{}^*=\sigma_x F_S^{-1}\left(1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}\right)+\mu_x \text{ and}$$

$$I^{ST_{j(ij)}}{}^*=\sigma_x\left[F_S^{-1}\left(1-\frac{c^{ST_j}}{r^G-c^{V_j}+c^{penalty}}\right)-F_S^{-1}\left(1-\frac{c^{ST_j}-c^{ST_i}}{c^{V_i}-c^{V_j}}\right)\right] \text{ respectively. } \blacksquare$$

Appendix F: Sensitivity Analysis

We provide sensitivity analysis on the parameters to illustrate the robustness of our findings. The analysis is performed by changing the values of four key parameters:

The proportion of total cost within the revenue- The default value used is 94%. The values tested are 95%, 96% and 97%. The corresponding graphs are shown in Figure E3-7 – E3-9. As this value increases, the profitability of *REC* and *IIC* decreases, whereas profitability of *RIC* is not impacted much. Thus, *RIC* becomes the best strategy for a larger spectrum of cv values, but the overall results are still consistent.

The proportion of variable cost within the total cost- If this value increases, the proportion of fixed cost within the total cost decreases as the sum of the two is 100%. The default value is 83%. The values tested are 84%, 85% and 86%. The corresponding graphs are shown in Figure E3-10 – E3-12. As this parameter value increases, *IIC* becomes relatively more profitable. This is because, with the same budget, we can invest in more new capacity. The overall results do not change in this case as well.

The budget.- This impacts only *REC* and *IIC*. The initial budget is increased by 5%, 10%, 15% and 20%. The corresponding graphs are shown in Figure E3-13 – E3-15. As the budget increases, *RIC* becomes less attractive compared to other strategies as they are less restricted by the budget. The general relationships still remain valid.

The penalty cost.- As penalty cost decreases, the profit for all the strategies increases, however, the main structure of the three functions does not change. Thus, the findings are not impacted. The default value is $1.5r^G$. The penalty cost is decreased to $1.4r^G$, $1.3r^G$, $1.2r^G$, and $1.1r^G$. The corresponding graphs are shown in Figure E3-17 – E3-20.

- **Sensitivity Analysis of Total Cost (TC) and Variable Cost for Sole Strategies**

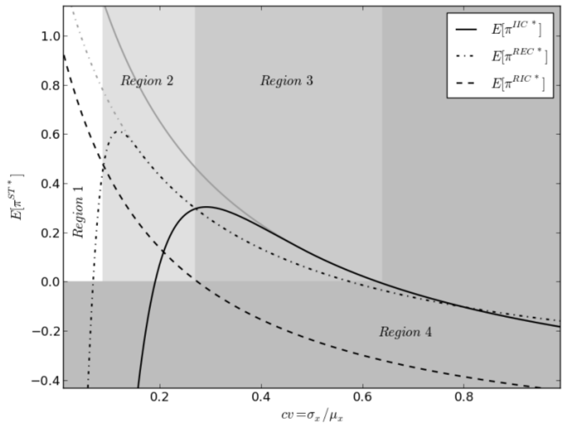

Figure E3-A1: TC is 95% of revenue

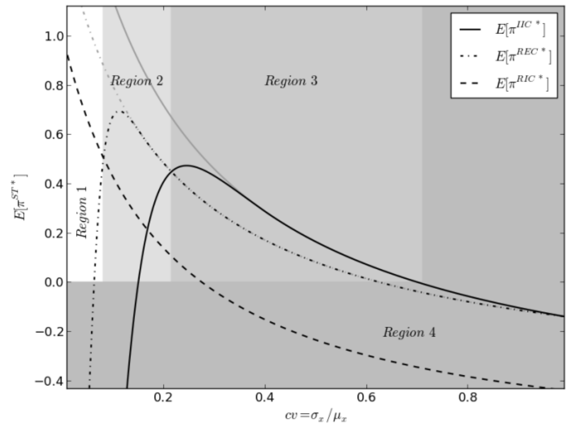

Figure E3-A2: var. cost is 84% of TC

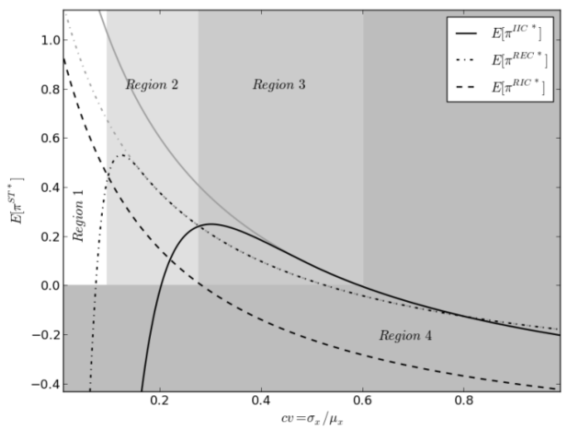

Figure E3-A3: TC is 96% of revenue

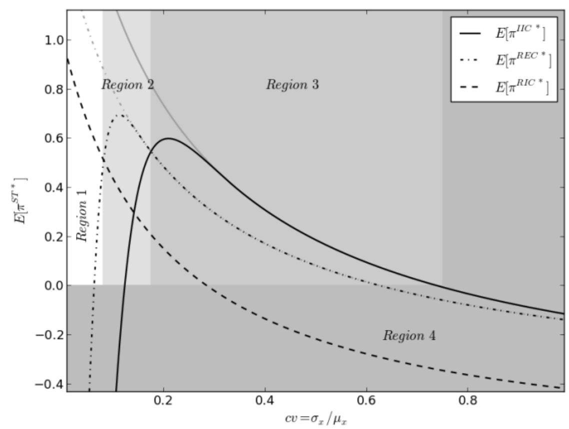

Figure E3-A4: var. cost is 85% of TC

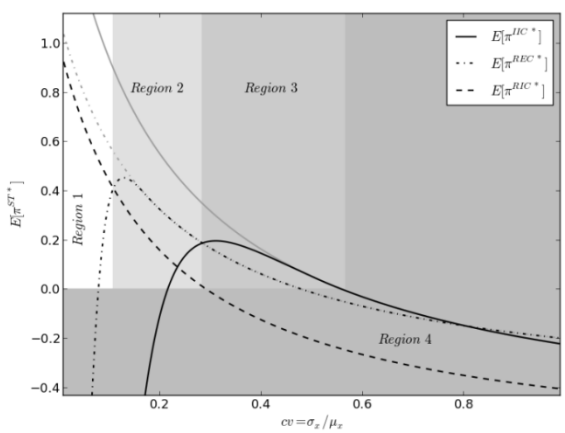

Figure E3-A5: TC is 97% of revenue

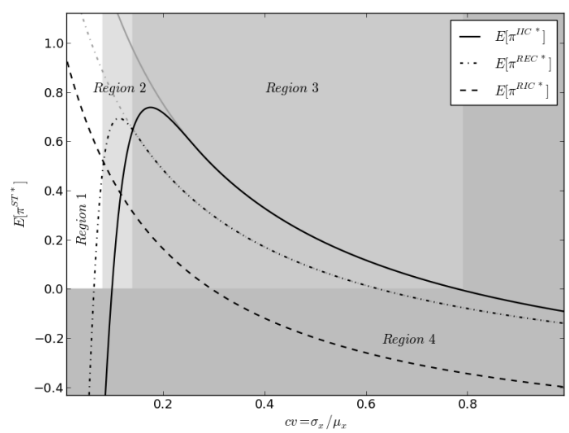

Figure E3-A6: var. cost is 86% of TC

- **Sensitivity Analysis of the Budget for Sole Strategies**

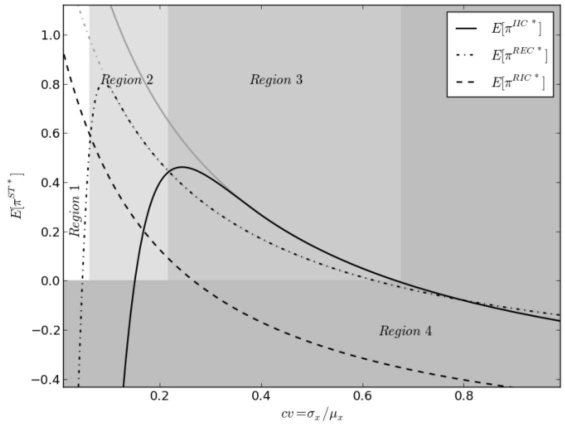

Figure E3-A7: 5% Increase

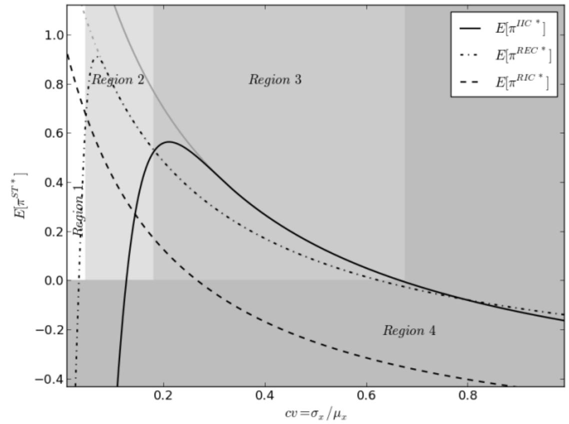

Figure E3-A8: 10% Increase

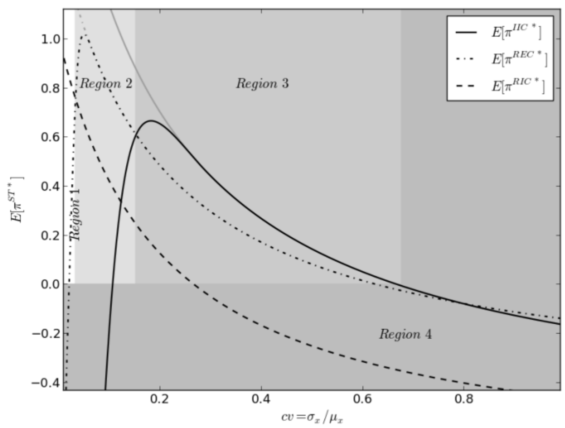

Figure E3-A9: 15% Increase

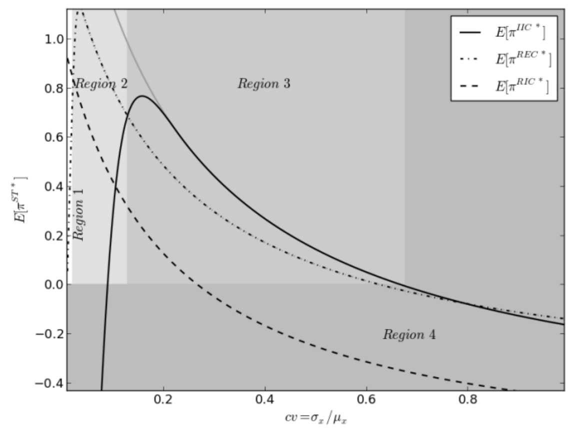

Figure E3-A10: 20% Increase

- **Sensitivity Analysis for the Penalty Cost for Sole Strategies**

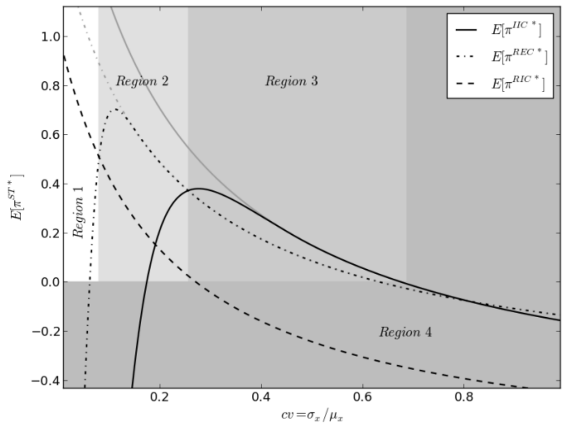

Figure E3-A11: $\boldsymbol{c}^{penalty} = 1.4\boldsymbol{r}^{\boldsymbol{G}}$

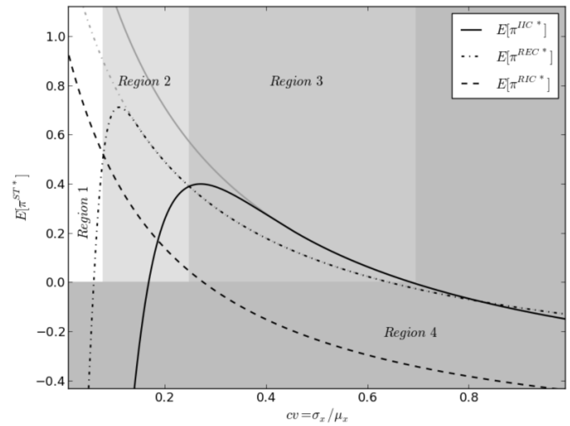

Figure E3-A12: $\boldsymbol{c}^{penalty} = 1.3\boldsymbol{r}^{\boldsymbol{G}}$

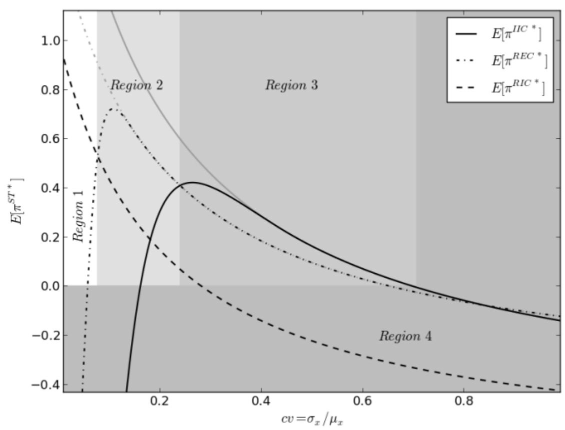

Figure E3-A13: $\boldsymbol{c}^{penalty} = 1.2\boldsymbol{r}^{\boldsymbol{G}}$

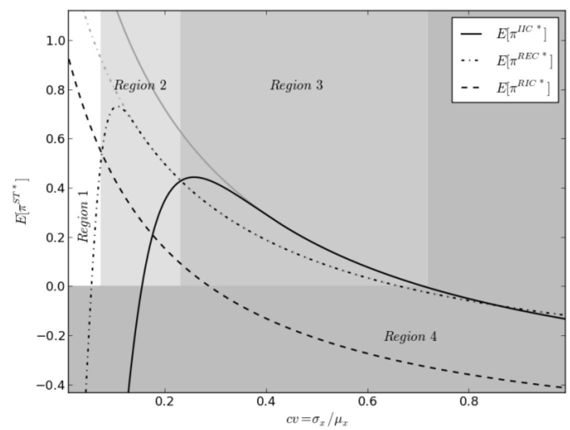

Figure E3-A14: $\boldsymbol{c}^{penalty} = 1.1\boldsymbol{r}^{\boldsymbol{G}}$

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