Sharing Information to Manage Perishables

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Abstract

We address the value of information (VOI) sharing in the context of a two–echelon, serial supply chain with one retailer and one supplier that provides a single perishable product to consumers. We evaluate information sharing under two supply chain structures where both supply chain members share their inventory levels and replenishment policies with the other. In the first structure, referred to as Decentralized Information Sharing, the retailer and the supplier make their own profit-maximizing replenishment decisions. In the second structure, referred to as Centralized Information Sharing, the replenishment decisions are coordinated. The latter supply chain structure corresponds to the industry practice of vendor–managed inventory. We measure the VOI as the marginal improvement in expected profits that a supply chain achieves relative to the case when no information is shared. Key assumptions of our model include stochastic demand, lost sales, and order quantity restrictions.

We establish the importance of information sharing in the supply chain and identify conditions under which relatively substantial benefits are realized. As opposed to previous work on the VOI, the major benefit of information sharing in our setting is driven by the supplier's ability to provide the retailer with fresher product. By isolating the benefit by firm, we show that sharing information is not always Pareto improving for both supply chain partners.

Keywords: value of information, vendor managed inventory, supply chain management, perishable inventory

1. Introduction

We place our research in the context of food and agribusinesses and specifically, in the grocery industry. The importance of perishable goods is growing in terms of sales, SKUs, and the competitive importance of attracting consumers. For supermarkets, perishables are the driving force behind the industry's profitability and represent a significant opportunity for improvement. Perishables account for more than half of supermarket sales or up to $150 billion a year, but also subject the firms to losses of up to 15 percent due to damage and spoilage. Further, the quality, variety and availability of perishables have become an order winning criteria of consumers, representing the primary reason many consumers choose one supermarket over another (Hennessy 1998b). While our research focus is on groceries, the management of perishable inventories is an important problem confronting many other industries including blood banks, food services, pharmaceuticals, chemicals, and increasingly, biotechnology. Yet the grocery industry is particularly appropriate, given the current practitioner activity and industry initiatives. This industry is characterized by a highly competitive business environment with low profit margins, low barriers to entry, the emergence of super centers and mass marketers, increasing consumer demand for high quality perishables, and stagnant industry growth (Saporito 1995). To help them compete in this competitive environment, many firms are investing in information enabling technologies for the management of their perishables. At the same time, the benefits from these investments remain unclear, as does the distribution of the benefits among the supply chain members.

In the current state of the industry, most individual supply chain members follow practices that maximize their own competitive positions, often at the expense of global system efficiencies. These practices include the wide–spread use of trade promotions, diverting, shipping full truck–loads, and minimum order quantity requirements. The inefficiencies arising from mismatches between supply and demand manifest as excessive inventory holding costs, increased product loss due to damage and spoilage, higher administrative costs, and higher manufacturing costs. According to Kurt Salmon Associates (1993), by correcting these adversarial and inefficient practices through an initiative known as Efficient Consumer Response (ECR), the grocery industry could realize annual savings in the amount of $30 billion.

The key to achieving the benefits of ECR is leveraging information technology to enable the use of timely and accurate information on a coordinated basis throughout the supply chain. While much attention has been focused on the technological infrastructure required to implement ECR initiatives, little attention has been placed on the application of information itself and the development of specific policies to combat the problems and inefficiencies inherent in current practices (Kurt Salmon Associates 1995). Nowhere is this more evident than in the management of perishables. Produce and most other perishables have lagged behind other products in ECR cost-saving strategies (Hennessy 1998a).

We explore the value of information for inventory replenishment (VOI) of a perishable product. Information may be shared among facilities in a supply chain and used in their decision making to improve performance. As in this study, the literature on the VOI develops information based replenishment policies and evaluates conditions where shared information is beneficial. Motivation for such research is predicated on the academic prescription that sharing information mitigates the Bullwhip Effect (Lee et al. 1997a,b), that enabling information technologies are widely available, and practitioner initiatives like Efficient Consumer Response (Kurt Salmon Associates 1993). Research by Chen (1998), Gavirneni et al. (1999), Cachon and Fisher (2000), Lee et al. (2000), and Moinzadeh (2002) are representative of recent contributions. As opposed to previous work on the VOI, the major benefit of information sharing in our setting comes from the supplier's ability to provide the retailer with fresher product. We are not aware of any other published research that addresses information sharing for a perishable product.

We address VOI in the context of a two–echelon, serial supply chain with one retailer and one supplier that provides a single perishable product to consumers. A distinguishing characteristic of perishables is that they have a finite lifetime and hence, the age of the products must be considered in their management. We assume that the product lifetime is fixed and deterministic once produced. Any unsold inventory remaining after the lifetime elapses must be discarded (outdated) at zero salvage value. We evaluate two scenarios of information sharing. The first scenario, named Decentralized Information Sharing, considers the case where both supply chain members share their inventory levels and replenishment policies with the other but each facility makes its own profit maximizing replenishment decision. The second scenario, named Centralized Information Sharing, considers the same scenario of information sharing, but where the replenishment decisions are coordinated. This second case corresponds to the practice of vendor–managed inventory (VMI). We formulate the respective scenarios as Markov Decision Processes (MDPs) and measure the VOI as the marginal improvement in expected profits that a supply chain achieves relative to the case when no information is shared. Key characteristics of our model include stochastic demand, lost sales and order quantity restrictions.

We establish the importance of information sharing in the supply chain and identify conditions under which relatively substantial benefits are realized. Through a numerical study, we find that by sharing information, total supply chain expected profits increase an average of 4.3% for a decentralized supply chain and 8.4% for a centralized supply chain. Through a sensitivity analysis, we give conditions where supply chains benefit the most from sharing information. By isolating the benefit by firm, we also show that sharing information is not always Pareto improving for both supply chain partners.

The rest of the paper is organized as follows. §2 reviews the literature. §3 defines the model. §4 presents our numerical study with discussion and §5 concludes the paper.

2. Literature Review

Our research draws on two separate research streams: the value of information and perishable inventory theory. In this section, we provide a review of prominent research in each stream and position our study at the point of their intersection.

2.1 Value of Information

The literature on the value of information in a multi-echelon supply chain context is nascent and continues to evolve from the broader literature on multi-echelon inventory systems. Contributions differ considerably along key assumptions that make direct comparisons between them difficult. Indeed, VOI reported among the set of disparate contributions varies considerably. Among the literature, major differences are exhibited in the assumptions of supply chain structure, what information is shared, how information is used, and whether decision–making is centralized or decentralized.

There are a few papers that explore VOI in serial supply chains. Bourland et al. (1996) study how sharing inventory data improves the supplier's ordering decisions with stationary stochastic demand. In their model, the VOI manifests itself in the supplier's ability to respond to the change in the retailer's inventory level, prior to the placement of the retailer's order. Chen (1998) compares echelon stock policies that require information sharing and centralized decision making with installation–stock policies that do not require information sharing and allow independent decision–making. Although he reports a cost improvement with an echelon policy by as much as 9%, on average the benefit is reported at 1.8%.

Gavirneni et al. (1999) explore the impact of a supplier's capacity restriction on the value of information. They develop two cases of information sharing. In the first case, the retailer shares information about underlying demand and the parameters of its order policy. In the second case, the retailer also communicates its inventory level. They report a high level of VOI when the retailer shares information about underlying demand and the parameters of its order policy but only an incremental additional benefit from sharing its inventory level.

Lee et al. (2000) address VOI in the context of non–stationary stochastic demand. Specifically, demand follows an AR(1) process and is correlated one period to the next. They show that sharing demand information can lead to substantial benefits, particularly when demand correlation is high. Raghunathan (2001), however, points out that the supplier's base stock policy used in Lee et al. (2000) without information sharing only utilizes the last observed order from the retailer. He shows that when the full history of orders is used, the VOI is negligible.

Other studies investigate the VOI in the context of a two echelon, arborescent supply chain consisting of one supplier and N identical retailers. These include Cachon and Fisher (1998), Aviv and Federgruen (1998), and Moinzadeh (2002). To our knowledge, we are the first to study VOI in a supply chain selling a perishable product.

2.2 Perishable Inventory Theory

The literature on perishable inventory theory is considerably older and extends back several decades. The principal distinction within the existing literature on perishable inventory is whether the product has a fixed or random lifetime. We review the key literature on fixed lifetime perishability since it is more closely related to our research and we refer the reader to Raafat (1991) for a comprehensive review of random lifetimes. Nahmias (1982) provides a good, albeit now dated, literature review of fixed lifetime perishable inventory models.

There are three problems addressed by the literature on fixed lifetime perishable inventory theory: determining reasonable and appropriate methods for issuing inventory, replenishing inventory, and in the case of arborescent multi–echelon systems, allocating inventory. Since inventory may contain units of different ages, the issuing problem focuses on the order in which units of each age category are withdrawn from inventory to satisfy demand. Early work by Derman and Klein (1958), Lieberman (1958), and Pierskalla and Roach (1972) collectively show the conditions where issuing the oldest items first (FIFO) and youngest items first (LIFO) are optimal. With constant product utility until outdating, as is the case in our model, FIFO issuing is optimal.

Significant research has been done to derive and evaluate the optimal replenishment policies for items with a fixed lifetime. When the product lifetime is one period, Arrow et al. (1958) show that the problem is equivalent to a series of simple newsboy problems. When the product lifetime is greater than one period, the problem is significantly more complicated because the quantity of inventory in each possible age category must be tracked. Van Zyl (1964) is credited as the first to derive an optimal policy when the product lifetime is two periods.

Nahmias (1975) and Fries (1975) extend and generalize Van Zyl's work by deriving and evaluating optimal policies for perishable products with lifetimes greater than two periods. They formulate their respective problems as cost–minimizing dynamic programs that include both outdating and shortage costs. In both cases, product is assumed to be fresh on receipt (i.e. fixed lifetime remaining). The optimal policy is shown to be non–stationary and dependent on the age distribution of the inventory. In our model, all units do not arrive fresh at the retailer; the remaining lifetime depends on the age of stock at the supplier used to satisfy a retail order.

Progress on the combined problem of multi–echelon inventory and perishable product inventory systems has been limited. We are aware of only a handful of contributions in this important area, the majority are motivated by the management of blood banks and focus almost exclusively on the allocation problem of how to divide the quantity of stock in each age category among multiple facilities. Yen (1965), Cohen et al. (1981) and Prastacos (1981) are representative examples in this area. In these contributions, as is the case with blood management, the replenishment supply of the product is random. In our study, it is deterministic.

More recently, Goh et al. (1993) consider a two–stage inventory system at a single facility that is also motivated by the management of blood banks. The first stage contains inventory of fresh blood and the second stage contains older, but still usable, blood. The issuing quantity to the second stage is automatically determined by the age of the blood from the first stage where both the supply and withdrawals of blood occur randomly. Demand requests specify whether they must be satisfied with fresh units or if older units are acceptable.

Fujiwara et al. (1997) provide the most recent contribution to the literature and the only one we are aware of that directly addresses perishable food products. They consider a two–stage inventory system at a single facility where the first–stage consists of the whole product (e.g. meat carcasses) that is made up of multiple sub–products (e.g. cuts of meat) while the second–stage consists solely of the sub–products. Exogenous demand occurs only at stage two, although unsatisfied stage two demand can be met by emergency issuing from stage one inventory at a cost premium. They derive optimal ordering and issuing policies for this scenario.

In the next section, we introduce a model that extends the research on perishable inventory systems by evaluating a serial system under the assumptions of batch ordering and lost sales: two highly significant and relevant aspects to the management of perishables in the grocery industry.

3. Model

The setting is a serial supply chain consisting of two echelons, a retailer and supplier that provide a single perishable product to consumers. We assume a periodic review inventory model for each facility, as this is the most common system used in the grocery industry. The product is perishable and has a deterministic lifetime of R periods. Throughout its lifetime, the utility of the product remains constant until the remaining lifetime is zero periods, after which the product expires and is outdated (disposed) without any salvage value. This assumption corresponds to the wide–spread use of product expiration dates on packaged goods such as fresh cut meat, dairy products, and packaged produce. We discuss the inventory replenishment policies for each echelon separately in the sections that follow.

For the retailer, the order of events each day follows the sequence: 1) receive delivery, 2) outdate inventory, 3) place order, and 4) observe and satisfy demand. Retail demand is discrete, stochastic, and stationary over time. Let D denote total demand in the current period, with probability mass function $\phi(\cdot)$. Further, let μ denote its mean and σ^2 its variance. Unsatisfied demand is lost.

To simplify notation, we normalize the retailer's revenue per unit of satisfied demand to one dollar and predicate the unit purchase cost on the product margin m_0, expressed as a percentage of unit revenue. A holding cost h_0 is assessed on ending inventory.

The replenishment decision d is restricted to either zero or Q units, where the batch size Q represents the bundle of units that are packaged, shipped, and sold together. The batch size Q captures certain economies of scale in transportation and handling. Although we do not model these economies explicitly (i.e., there is no fixed order cost) we nevertheless evaluate the impact of this important parameter in our analysis. Clearly, a more robust design would enable ordering in multiples of Q, as in the familiar R, nQ policy, but doing so causes our problem to become intractable. Specifically, our restriction on the order size enables us to track the age of product as it moves between echelons, which is a key modeling contribution and one that has yet to be achieved in the literature. We are not aware of any research that provides exact analysis of a multi-echelon inventory system for a perishable product with batch ordering.

Notwithstanding, we note that our assumption is common in the literature on the value of information (see Moinzadeh 2002, Cachon and Fisher 2000, Chen 1998, and Van der Duyn Schouten et al. 1994) for non-perishable products. At the same time, a fixed batch size is also commonly observed in practice for perishable items. In the grocery industry, given the extreme level of product variety, there are thousands of low volume products where a single batch of replenishment is more than sufficient to satisfy expected demand during the order cycle. Hence, from a practical perspective, we further assume values for μ and σ^2 such that demand during an order cycle rarely exceeds Q.

The replenishment lead-time is one period. Since the product is perishable, inventory may be composed of units with different ages. Let i_x denote inventory, after outdating and before demand, that expires in x periods, where $x = 1, \ldots, M$ and $M \equiv R - 1$ is the maximum product shelf life at the retail echelon. Let $\vec{i} = (i_1, i_2, \ldots, i_M)$ represent the vector of inventory held at each age class and define $I = \sum_{x=1}^{M} i_x$. For ease of exposition, let $(z)^+ \equiv \max(z, 0)$ and z' denote a variable defined for the next period, whereas a plain variable z is defined for the current period. For example, i'_x represents the retailer's inventory next period that expires in $x+1$ periods from the current period. Demand is satisfied using a FIFO inventory issuing policy and inventory is not capacitated.

For the supplier, the order of events each period follows the sequence: 1) receive delivery, 2) observe and satisfy demand, and 3) place order. The retailer's order quantity corresponds to the supplier's demand in the same period. Since the supplier only observes orders of Q units and faces no ordering cost, the supplier replenishes in orders of Q units. Thus, the supplier faces uncertainty only in the timing of the order arrivals. We assume that the supplier orders from a perfectly reliably exogenous source (i.e. the outside source has ample capacity) and the lead-time is one period (i.e. whenever Q units are ordered they become available at the start of the next period). If the supplier receives an order and does not have units in stock to fulfill it, the supplier pays an expediting charge that allows it to meet the order in the same period. Thus, the retailer always receives its order request one period after placing it.

The supplier's replenishment policy corresponds to a time phased order point policy incorporating safety lead-time. This policy is optimal for a firm facing intermittent demand with deterministic quantities, uncertain timing, and non–perishable inventory (Silver et al. 1998). It is also the optimal policy for the supplier since no outdating occurs at the supplier's location. This is because the longest possible time between retail orders is M periods (the maximum shelf life of the product at the retailer) and, at that time, the age of product at the supplier has a minimum life of two periods remaining. Note that this assumption requires a further condition that the retailer will never intentionally go through a period with zero inventory, thus assuring the interval between retail orders never exceeds M periods. Although restrictive, our assumptions are supported by industry where 1) outdating at supplier echelons is trivial compared to the retail echelon and 2) their exists a strong emphasis on high retail in-store availability.

3.1 No Information Case

We begin by establishing a base case where the retailer does not periodically share information pertaining to its replenishment process or inventory position. We also assume that both members know the underlying demand distribution. We next formulate the retailer's MDP and then express the supplier's objective and expected long–run average profit.

3.1.1 No Information Case: Retailer's Policy

We formulate the retailer's No Information Case (NI Case) replenishment problem as a MDP where its objective is to find an optimal reorder policy such that its expected profit is maximized. The linkage between periods is captured through the one period transfer function of the retailer's age dependent inventory. This transfer is dependent on the current inventory level, any order placed in the current period, the realization of demand D in the current period, and the remaining lifetime of any replenishment inventory (this determines the position x within the vector $\vec{i}$ that is updated with the replenishment quantity). The age of the product replenishment is a function of the number of periods since the last retailer order L where $L \in \{1, 2, ..., R\}$, and the supplier's safety lead–time α (described in the next section on the supplier's policy). For convenience, let A denote the remaining life of the inventory on receipt at the retailer, where $A \in \{1, 2, ..., M\}$.

Let $\vec{i}'$ denote the retailer's inventory level in the next period and $\tau\left(\vec{i}, D, d, A\right)$ denote the one period transfer function. Then $\vec{i}' = \tau\left(\vec{i}, D, d, A\right)$ where

$$i'_x = \begin{cases} \left(i_{x+1} - \left(D - \sum_{z=1}^{x} i_z \right)^+ \right)^+ & 0 < x < A \\ d & x = A \end{cases}$$

We now introduce the retailer's MDP. The value $\bar{c}$ is the equivalent average return per period when an optimal policy is used. The extremal equations are

$$f\left(\vec{i}, L\right) + \bar{c} = \max_{d \in \{0, Q\}} \left\{ \sum_{D=0}^{\infty} \left[\min\left(D, I\right) - d\left(1 - m_0\right) - h_0\left(I - D\right)^+ + f\left(\tau\left(\vec{i}, D, d, A\right), L'\right) \right] \phi\left(D\right) \right\} \quad (1)$$

where

$$A = \begin{cases} M & L \le \alpha \\ M - L + \alpha + 1 & L > \alpha \end{cases} \quad (2)$$

$$L' = \begin{cases} 1 & d = Q \\ L + 1 & d = 0 \end{cases} \quad (3)$$

Since the state and decision spaces are discrete and finite and profit is bounded, there exists an optimal stationary policy that does not randomize (Putterman, 1994). The left hand side of equation (1) defines an extremal equation by the vector of inventory $\vec{i}$ and the number of periods L since the last order was placed. The right hand side of equation (1) computes the total expected profit that is composed of revenue from satisfied demand, the purchase cost associated with any new order, holding cost on ending inventory, and future expected profit. Equation (2) determines the remaining lifetime of any receipts. Note that if $L \le \alpha$, then $A = M$ since the supplier must replenish the retailer's order through expediting. Also, equation (2) assumes that the retailer knows both the supplier's safety lead–time α and the age of replenishment A. The retailer can readily deduce these values given the replenishment history with the supplier. Finally, equation (3) updates the number of periods since the last order was placed, predicated on whether or not an order is placed in the current period.

3.1.2 No Information Case: Supplier's Policy

Since the retailer is restricted to ordering Q units at a time then the supplier will only replenish in batch sizes of Q units and the supplier's decision involves only the timing of its replenishment, determined during periods that it ends with zero units in inventory. Thus, a sample path of the supplier's inventory level follows a renewal process with the renewal occurring each time the retailer places an order. The supplier's objective is to make an ordering decision that minimizes its inventory related cost over this renewal cycle.

Since the supplier is only concerned with the timing of its replenishment, the problem reduces to a myopic cost minimization problem that the supplier faces each period it ends with zero units in inventory. If the supplier does not place an order during one of these periods, it risks paying an expediting charge of b if the retailer places an order next period. If the supplier does place an order and the retailer does not order the next period, the supplier pays a holding cost of h_1 for each of the Q units it holds. Obviously, if the number of periods since the supplier's last replenishment is equal to the lifetime of the product then the supplier knows that the retailer will place an order. Let L' represent the number of periods since the supplier last replenished and λ represent the supplier's decision to place an order where $\lambda = 1$ corresponds to an order being placed and $\lambda = 0$ corresponds to a decision not to order. Also, let d' denote the retailer's expected order in the next period. The supplier's expected inventory related cost for the next period depends on the conditional probabilities that the retailer places an order next period $P(d' = Q \mid L' < R)$ or not $P(d' = 0 \mid L' < R)$ given that the number of periods since the supplier last replenished is less than *R*. The supplier's objective is

$$\min_{\lambda \in \{0,1\}} (1-\lambda)(b * P(d' = Q \mid L' < R)) + \lambda(h_1 Q * P(d' = 0 \mid L' < R)).$$

It is straight–forward to show that the supplier's optimal policy is

$$\lambda^* = \begin{cases} 1 & if \quad L' = R \\ 1 & if \ P(d' = Q \mid L' < R) \geq \frac{h_1 Q}{b + h_1 Q} \\ 0 & \qquad otherwise \end{cases}.$$

Note that we assume that the supplier acts honorably and does not attempt to increase its profit by ordering earlier than its safety lead-time so that the product's useful life at the retailer will be shorter, forcing the retailer to order more frequently. While there may be a short-term incentive for the supplier not to act in this manner, the long-term negative consequences do not typically make it worthwhile, as the retailer would eventually figure out the supplier's deceitfulness.

It remains to characterize the probability $P(d' = Q \mid L' < R)$. Under no information sharing, the supplier only knows the order size of the retailer *Q*, the final customer demand distribution $\phi(\cdot)$, and the number of periods since the retailer's last order *L*. Without having details on the inventory position of the retailer and assuming that the retailer uses a reorder point system, the supplier estimates that each shipment brings the retailer's stocking level to $Q - \mu$ above its reorder point. An expected demand for one period is subtracted from the order quantity in this estimate to account for the one period delivery lead-time. This estimate is an unbiased forecast as long as $(Q - \mu)/\mu$ is an integer. Under these conditions, the probability that the retailer places an order next period is

$$P(d' = Q \mid L' < R) = P(\sum_{1}^{L'} D \geq Q - D) = \sum_{D=\omega}^{\infty} \phi(D)$$

where ω represents the closest integer to Q/L . Note also that

$$P(d'=0\,|\,L'<R)=1-P(d'=Q\,|\,L'<R)=\sum_{D=0}^{\omega}\phi(D)\,.$$

To find the supplier's expected per period inventory related cost, we translate the supplier's optimal policy into its safety lead-time based on its forecasted distribution of the time between the retailer's orders. Define $\tilde{D}=Q/D$ as a random variable representing the number of periods between the retailer's orders. Let $\Phi_{\tilde{D}}$ represent the cdf of $\tilde{D}$ which has a mean of Q/μ and a variance of $\frac{Q\sigma^2}{\mu}$. The supplier's safety lead-time is based on its critical fractile, determined from its cost of being early or late with a replenishment order. Finally, recall that α represents the number of periods the supplier waits after receiving an order before it places a replenishment order. The choice of α depends only on the supplier's safety lead-time based on its critical fractile (determined from its cost of being early or late with a replenishment order). As it is impossible by our assumptions on the retailer's policy that α will exceed the product's lifetime, the supplier places its own replenishment order $\alpha=\Phi_{\tilde{D}}^{-1}(\frac{h_1 Q}{b+h_1 Q})$ periods after receiving a retail order.

To express the supplier's expected profit per period, some additional notation is required. Let $\pi_{\vec{i},L}$ denote the steady state probability that the retailer is in state $(\vec{i},L)$. Let m_1 denote the supplier's margin per unit expressed as a percentage of its unit revenue, and let $d^*_{\vec{i},L}$ be the optimal retailer replenishment decision for state $(\vec{i},L)$. Then, the supplier's expected profit per period is

$$\sum_{\vec{i}}\sum_{L}\Big[m_0\left(1-m_1\right)d^*_{\vec{i},L}-b\left(\alpha-L+1\right)^+-h_1\left(Q-d^*_{\vec{i},L}\right)^+w\left(L-\alpha\right)\Big]\pi_{\vec{i},L}$$

where

$$w\left(L-\alpha\right)=\begin{cases}0 & L-\alpha\le 0\\ 1 & L-\alpha>0\end{cases}.$$

3.2 Decentralized Information Sharing Case

In the Decentralized Information Sharing Case (DIS Case) both the retailer and the supplier share their inventory state and replenishment policy with the other, but each facility continues to make its own replenishment decisions to maximize its own expected profit. As before, we start by formulating the retailer's MDP and then express the supplier's objective and expected long–run average profit.

3.2.1 Decentralized Information Sharing Case: Retailer's Policy

The retailer's optimization is similar to that expressed for the NI Case. However, since the supplier's replenishment decision is now state–dependent on the retailer's inventory position, it is necessary to track the supplier's inventory state. Let G denote the supplier's inventory state (modified to account for the lead-time to the retailer) in the current period after any receipts and before an order is satisfied, where G represents the remaining life of the product batch, minus one period. Hence, $G\in\left\{0,1,...,M\right\}$ and $G=0$ corresponds to the state when no units are in inventory. Since we now track the supplier's inventory directly, we drop L (the periods since the last retailer order) from the state space. The extremal equations are

$$f\left(\vec{i},G\right)+\bar{c}=\max_{d\in\{0,Q\}}\left\{\sum_{D=0}^{\infty}\left[\min\left(D,I\right)-d\left(1-m_0\right)-h_0\left(I-D\right)^{+}+f\left(\tau\left(\vec{i},D,d,A\right),G'\right)\right]\phi\left(D\right)\right\} \quad (4)$$

where

$$A=\begin{cases}M & G=0\\ G & G>0\end{cases} \quad (5)$$

and

$$G' = \begin{cases} 0 & \lambda = 0, d > 0 \\ G-1 & \lambda = 0, d = 0 \\ M & \lambda = 1 \end{cases}. \tag{6}$$

Note that equation (5) determines the remaining life of the receipts at the retailer predicated on the inventory state of the supplier. Equation (6) determines the supplier's inventory state in the next period, predicated on both the retailer's order and the supplier's replenishment decision. It remains to determine the supplier's replenishment decision. As with the NI Case, the supplier's objective is to make an ordering decision that minimizes its next period inventory related cost. With information sharing, the supplier knows the retailer's current state and replenishment policies and can use this information in its decision–making

3.2.2 Decentralized Information Sharing Case: Supplier's Policy

Under the DIS Case, the supplier's objective is

$$\min_{\lambda \in \{0,1\}} \ (1-\lambda)(b * P(d' = Q \,|\, \vec{i}, G)) + \lambda(h_1 Q * P(d' = 0 \,|\, \vec{i}, G))$$

which gives an optimal policy of

$$\lambda^* = \begin{cases} 1 & if \ P(d' = Q \,|\, \vec{i}, G) \geq \frac{h_1 Q}{b + h_1 Q} \\ 0 & otherwise \end{cases}.$$

The conditional probabilities $P(d' = Q \,|\, \vec{i}, G)$ and $P(d' = 0 \,|\, \vec{i}, G)$ are functions of the retailer's one period inventory state transition probabilities. Specifically, let $\theta\left(\vec{i}' \,\middle|\, \vec{i}, G\right)$ denote the retailer's one period state transition probability into state $\vec{i}'$ conditional on the system state $\left(\vec{i}, G\right)$ in the current period. Note that $\theta\left(\vec{i}' \,\middle|\, \vec{i}, G\right)$ is a simple function of $\phi(D)$:

$$\theta\left(\vec{i}'\middle|\vec{i},G\right)=\sum_{D=0}^{\infty}\phi\left(D\right)w\left(\vec{i}',\tau\left(\vec{i},D,d^*_{\vec{i},G},A\right)\right)$$

where A is given by equation (5) and

$$w\left(\vec{i}',\tau\left(\vec{i},D,d^*_{\vec{i},G},A\right)\right)=\begin{cases}0 & \vec{i}'\neq\tau\left(\vec{i},D,d^*_{\vec{i},G},A\right)\\ 1 & \vec{i}'=\tau\left(\vec{i},D,d^*_{\vec{i},G},A\right)\end{cases}.$$

Then

$$P(d'=Q\left|\vec{i},G\right.)=\sum_{\vec{i}'}\theta\left(\vec{i}'\middle|\vec{i},G\right)\middle|d^*_{\vec{i}',G'}=Q$$

where G' is given by equation (6).

Since the retailer and supplier replenishment decisions are inter-related and decision–making is decentralized, some discussion is warranted regarding the order in which the values for d^* and λ^* are determined. We employ the following solution procedure. Given a system state $\left(\vec{i},G\right)$, we first condition on the decision $d=0$ and compute the optimal supplier policy $\lambda^*\left|d=0\right.$. Then, we compute the corresponding expected average profit for the retailer given these decisions. Next, we provide the same treatment to the condition for the decision $d=Q$ and find both the optimal supplier policy $\lambda^*\left|d=Q\right.$ and the associated expected average profit for the retailer. Since we then have the optimal supplier decision for each retailer decision along with the corresponding expected average profit for the retailer, we simply choose the value d^* that maximizes the retailer's expected profit.

As in the NI Case, the supplier's expected average profit per period is determined from the limiting behavior of the retailer in steady state. Letting $\pi_{\vec{i},G}$ denote the steady state probability that the system is in state $\left(\vec{i},G\right)$ and $d^{*}_{\vec{i},G}$ denote the optimal retailer replenishment decision for state $\left(\vec{i},G\right)$, the supplier's expected profit per period is

$$\sum_{\vec{i}}\sum_{G}\left[m_0\left(1-m_1\right)d^{*}_{\vec{i},G}-b\left(d^{*}_{\vec{i},G}-w\left(G\right)\right)^{+}-h_1\left(w\left(G\right)-d^{*}_{\vec{i},G}\right)^{+}\right]\pi_{\vec{i},G}$$

where

$$w\left(G\right)=\begin{cases}0 & G=0\\ Q & G>0\end{cases}.$$

3.3 Centralized Information Sharing Case

In the Centralized Information Sharing Case (CIS Case), a central decision maker seeking to maximize total supply chain profits makes replenishment decisions for both the retailer and the supplier. This corresponds to the practice of vendor–managed inventories (VMI). The decision variables for the MDP now include the supplier's replenishment order λ. Note that if it is optimal for the supplier to place an order in a period where it already has Q units in inventory, the existing inventory is immediately disposed. We note, however, that this scenario has never occurred in our numerical studies. For ease of exposition, let $c_1=Q\left(1-m_0\right)\left(1-m_1\right)$ denote the supplier's purchase cost. The extremal equations are

$$f\left(\vec{i},G\right)+\bar{c}=\max_{d\in\left(0,Q\right),\lambda\in\{0,1\}}\left\{\sum_{D=0}^{\infty}\left[\begin{array}{l}\min\left(D,I\right)-c_1\lambda-\left(c_1+b\right)\left(d-w\left(G\right)\right)^{+}\\ -h_0\left(I-D\right)^{+}-h_1w\left(G\right)+f\left(\tau\left(\vec{i},D,d,A\right),G'\right)\end{array}\right]\phi\left(D\right)\right\}. \quad (7)$$

Since the objective is to maximize system–wide profit, the optimization expressed in equation (7) omits the transfer price between the supplier and the retailer. Instead, expected profit maximized in the MDP is the sum of revenue received for satisfied demand, the purchase cost to the supplier for regular replenishment, the purchase cost plus penalty cost for any supplier expediting, holding costs applied to ending inventory for both facilities, and future expected profit. Note that equations (5) and (6) carry–over from the DIS Case and are not repeated here.

4. Numerical Study

We evaluate VOI in the two respective cases of information sharing (DIS and CIS) where VOI is measured as the % improvement in expected total supply chain profit, relative to the NI Case. Specifically,

$$VOI_{DIS} = \frac{\left(E\left[\text{Profit}_{DIS}\right] - E\left[\text{Profit}_{NI}\right]\right)}{E\left[\text{Profit}_{NI}\right]} \text{ and } VOI_{CIS} = \frac{\left(E\left[\text{Profit}_{CIS}\right] - E\left[\text{Profit}_{NI}\right]\right)}{E\left[\text{Profit}_{NI}\right]}.$$

Consumer demand $\phi(\cdot)$ corresponds to a truncated negative binomial distribution with a maximum value of 50 (any probabilities for demand exceeding 50 are redistributed proportionately within the truncated limit of the distribution). See Nahmias and Smith (1994) regarding the advantages of assuming negative binomial distributions for retail demand. Across our numerical experiments, the mean of the distribution is held constant at two and the variance–to–mean ratio (*VarMean*) is treated as a parameter to the model using the values reported below. Each period represents a week and the holding cost at each echelon is 25% of the purchase cost, measured on an annual basis. In total, we consider 486 experiments that comprise a factorial design for all combinations of the following parameters:

VarMean	1.5, 2.0, 3.0
R	5, 6, 7
Q	4, 5, 6
m_0	0.4, 0.5, 0.6
m_1	0.4, 0.5, 0.6
b	$0.05c_1$, $0.10c_1$

Our selection of parameter values is based on common values observed in practice for many dairy products and packaged produce items. At the same time, our selection is constrained by the computational feasibility of the resulting MDP, since the size of the state space expands exponentially with the vector of age–dependent inventory. Current and available computing technology enable us to solve a MDP of approximately one million states within three hours.

For each experiment, we use value iteration to compute the results for the respective MDPs and then solve the accompanying state transition matrices using the method of Gaussian elimination to evaluate steady state behavior as described in Kulkarni (p. 124). In §4.1, we discuss our general observations, in §4.2, we use an illustrative case to highlight several interesting results, and in §4.3, we report the results of our sensitivity analysis.

4.1 Computational Results and Observations

In general, we find that information sharing leads to a considerably fresher product for sale at the retailer and, as a consequence, information can be quite valuable. In Table 4.1, we report the VOI for the entire supply chain and for each individual member under a decentralized and centralized structure, at given percentiles of the 486 experiments. For example, the 0.50 percentile denotes the median values for VOI.   From this table, three observations emerge. First, when looking at the change in total supply chain profit, VOI is lower in the DIS Case than in the CIS Case, although it can still be quite substantial. Second, the benefits of information sharing are not shared equally between the retailer and the supplier. In both cases, the retailer receives the larger average benefit. Third, while total supply chain profit always increases with information sharing, either facility may individually realize a decrease in expected profitability. The impact of information sharing on both facilities depends largely on system behavior as we discuss separately for each case below.

Table 4.1: Value of Information Across Experiments

	DIS Case			CIS Case		
Percentile	Total	Retailer	Supplier	Total	Retailer	Supplier
0.00	0.0%	1.6%	-15.3%	1.4%	-8.1%	-11.0%
0.05	0.5%	3.1%	-11.5%	2.6%	1.7%	-3.6%
0.25	1.9%	5.8%	-6.2%	4.7%	4.7%	-0.2%
0.50	3.5%	10.1%	-4.3%	6.9%	10.1%	2.4%
0.75	6.0%	16.7%	-2.9%	10.9%	17.7%	6.5%
0.95	10.5%	40.4%	-0.2%	18.4%	38.4%	13.3%
1.00	21.7%	154.5%	6.6%	26.7%	205.4%	23.6%
Mean	4.3%	15.5%	-4.6%	8.4%	15.0%	3.3%

4.1.1 DIS Case

In the DIS Case, information sharing enables the supplier to better time the arrival of its replenishment with the timing of retail orders. In turn, the freshness of product (measured in terms of the expected average lifetime remaining) replenished at the retailer increases from an average of 4.8 periods to 5.6 (15.7% increase). In turn, outdating at the retailer decreases by an average of 28.4%. This increased product freshness also enables the retailer to boost its service level, albeit, by only 1.6% on average. Consequently, this small increase in satisfied demand combined with the large reduction in outdating results in a net decrease of retail orders to the supplier. We observe that retail orders decrease on average from 2.27 to 2.16 units per period (-4.6%). As a result, the supplier, on average, is worse off with a decline of 4.6% in its expected profit. Even though the supplier is able to reduce its expected inventory related costs through information sharing, these savings are trivial compared to its loss of revenue. The supplier, however, is not always worse off. When the increase in the retailer's service level provides an increase in the units of satisfied demand, exceeding the reduction in outdating, there is a net increase in retail orders to the supplier. We observe a profit increase of the supplier as high as 6.6%.

4.1.2 CIS Case

When information sharing is combined with centralized decision–making, we observe a larger VOI than in the DIS Case. On average, the VOI is 95% greater. There are two effects at work here. First, with coordinated replenishment there is little-to-no value in holding inventory at the supplier. In turn, the supplier serves a cross–docking function wherein any replenishment it receives is immediately sent onward to the retailer. We observe an average decrease of 60% in the supplier's expected inventory holding costs and a related average improvement of 22% in the freshness of the product delivered to the retailer. Note that this represents nearly a 6% improvement in product freshness relative to the DIS Case.

The second effect of coordinated replenishment comes from the elimination of double marginalization (the stocking decision at the retailer is predicated on the entire supply chain's profit, not just the retailer's as in the NI and DIS Cases). Consequently, the retailer's service level increases an average of 7.1%. This represents a considerable improvement when compared to the 1.6% average increase observed in the DIS Case.

There are also two significant second order effects resulting from the retailer's increased service level. First, the higher service level often provides a net increase in retail orders to the supplier, even when accounting for the reduction in outdating that arises from a fresher product, so, on average, the supplier is better off in the CIS Case. Note that the supplier's average expected profit declines by 4.6% in the DIS Case and increases by 3.3% in the CIS Case.

Second, to provide the higher level of service the retailer holds a greater level of inventory and can therefore experience an increase in outdating relative to both the NI Case and DIS Case. This can occur despite the fresher replenishment that arises from coordination and hence it is possible for the retailer to be worse off in the CIS Case, albeit, for a small number of cases as reported in Table 4.1. When we compare the retailer's expected profit between the CIS Cases and DIS Cases, we observe an average decrease of 0.3%, although the impact ranges between –32.3% and +20.0%.

In the next section, we clarify some of the unique observations using an illustrative example from our set of experiments.

4.2 Illustrative Example

We select the experiment where $Q = 4$, $R = 6$, $m_0 = 0.4$, $m_1 = 0.6$, $b = 0.10c_1$, and $VarMean = 3.0$ to highlight some interesting findings. In Table 4.2 we report the expected values for various performance metrics that include profit and its components, service (fill rate), product freshness, unit outdating, unit sales, and units ordered per period. In the DIS Case, the VOI is 1.3%, while the VOI is 9.1% in the CIS Case.

Table 4.2: Illustrative Example

	Retailer			Supplier		
Performance Metric	**NI Case**	**DIS Case**	**CIS Case**	**NI Case**	**DIS Case**	**CIS Case**
Revenue	1.700	1.716	1.902	1.243	1.195	1.441
Purchase Cost	1.243	1.195	1.441	0.497	0.478	0.577
Holding Cost	0.011	0.012	0.020	0.005	0.002	0.003
Expediting Cost	-	-	-	0.000	0.011	0.004
Profit	0.445	0.498	0.436	0.741	0.703	0.858
Service (Fill Rate)	0.850	0.858	0.951	1.000	1.000	1.000
Product Freshness	2.656	3.056	2.668	5.070	5.726	5.810
Unit Outdating	0.372	0.275	0.500	-	-	-
Unit Sales	1.700	1.716	1.886	2.072	1.991	2.402
Units Ordered	2.072	1.991	2.402	2.072	1.991	2.402

First with respect to the DIS Case and relative to the NI Case, observe in Table 4.2 that the supplier is able to increase its level of product freshness to the retailer by 12.9%. In turn, the retailer provides a fresher product to consumers (15.1%), decreases its level of outdating (-26.1%), and increases its level of service (1.0%), hence, improving its expected profit by

11.9%. The large reduction in outdating and small increase in unit sales results in a net decrease of 3.9% in retail orders to the supplier. As a consequence, the supplier observes a net decrease in revenue and a corresponding decrease in profit of 5.1%. The retailer's improvement offsets the supplier's loss so that total supply chain profit increases by 1.3%.

With respect to the CIS Case and relative to the NI Case, we observe that coordination with information sharing enables a 14.6% improvement in the freshness of the retailer's replenishment and an 11.9% increase in the retailer's service level. The increase in service arises from both a fresher product and the optimization of service levels with respect to the total supply chain's margins. Consequently, the retailer holds a substantially higher level of average inventory and actually realizes an increase in unit outdating of 34.3% – even with a fresher product for sale. The result is a 2.0% decrease in the retailer's expected profit. The supplier, however, benefits from both increases in the retailer's service level and increased outdating. Retail orders increase by 15.9% providing a corresponding 15.8% increase in the supplier's expected profit. Here, the supplier's improvement offsets the retailer's loss so that the total supply chain's expected profit increases by 9.1%.

This illustrative example highlights a significant swing in fortunes for each facility between the DIS Case and the CIS Case. In the DIS Case, the retailer observes a substantial increase in profit (11.9%) from information sharing but the supplier is worse off (-3.9%). The converse of this situation arises in the CIS Case where the retailer is worse off (-2.0%) and the supplier is better off (15.8%). We note that in a majority of CIS cases, both facilities are better off. In less than 5% of the cases reported in Table 4.1 do we observe that the retailer is harmed through information sharing. Nevertheless, it is clear that the benefits of information sharing are not equally shared. Also, it is clear that even when one facility is harmed, the supply chain as a whole is better off in both cases of information sharing. An important avenue for future research is to explore how certain contracts and incentives can be implemented so that the maximum benefits from information sharing can be realized and pareto improving. Clearly, without such arrangements, it is doubtful that both parties will be willing participants.

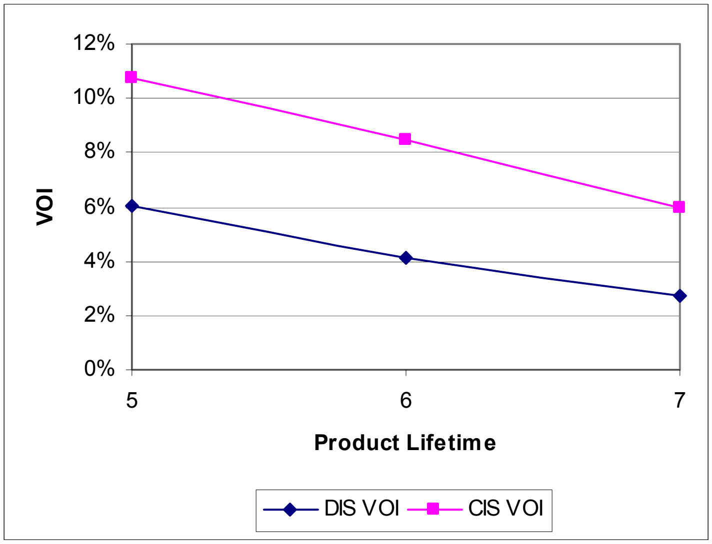
4.3 Sensitivity Analysis

The VOI in the two cases of information sharing covers a wide range as observed in Table 4.1. Generally, we find that VOI increases as a function of product perishability, the ability of the retailer to match supply and demand, and the size of the penalty for mismatches in supply and demand. We discuss and explain these relationships below.

4.3.1 Product Perishability

In Figure 4.1, we report the sensitivity of VOI to the product lifetime *R*. For each level of *R*, we average the values of VOI across all experiments for each case of information sharing. Clearly, VOI decreases with respect to increases in the product lifetime. The main benefit of information sharing is the supply of fresher product to the retailer. When the product lifetime is short, improvements in product freshness have a larger impact on the retailer's service level than when the product lifetime is long. Improvements in product freshness reduce the potential for outdating, allowing the retailer to carry more inventory for the same amount (or less) of product outdating which results in higher sales so that the entire supply chain is better off.

Figure 4.1: Sensitivity to Product Lifetime R

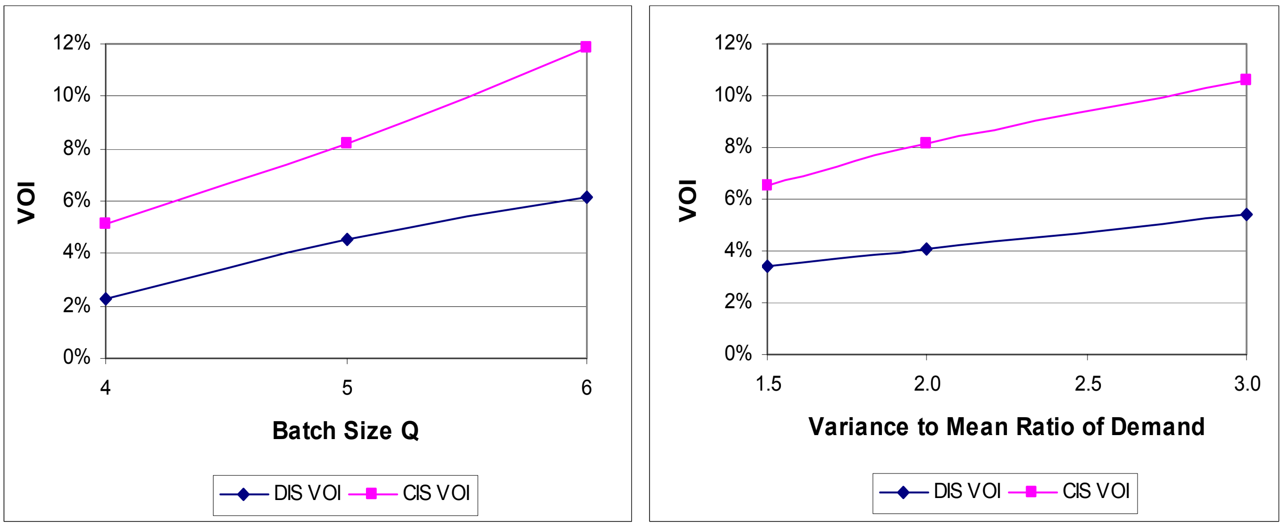


In contrast, long product lifetimes result in small VOI since the prospect of outdating is small. In this scenario, service levels are higher and outdating is lower so that any improvement in product freshness will not materially change the retailer's behavior. To see this, consider the extreme case of a non-perishable product. Here, there is no outdating. Hence, information sharing has no effect on retailer behavior because 1) it always receives its replenishment in full with a one period lead-time and 2) product freshness is no longer material to the problem. The only benefit of information sharing is to improve the supplier's ability to minimize its own related inventory costs. Yet, these costs typically represent a small portion of total supply chain cots. Consequently, VOI is negligible in this case.

4.3.2 Matching Supply and Demand

Two factors that affect the retailer's ability to efficiently match supply with demand are demand uncertainty, measured as the variance to mean ratio of demand (*VarMean*), and the batch size Q. In Figure 4.2, we graphically illustrate the relationship between these two parameters and VOI for each case of information sharing. Clearly, as the values for these parameters increase, so does VOI. This occurs because the more difficult it is for the retailer to match supply with demand, the more that product perishability becomes an issue. That is, the potential for product outdating increases when either demand is more uncertain or the replenishment batch size is larger. To demonstrate, we again look at an extreme case where $VarMean = 0$ and $Q = 1$, demand is deterministic and the retailer orders D units every period. In this scenario, the retailer fully satisfies demand and incurs no inventory related costs. Hence, VOI is zero.

Figure 4.2: Sensitivity to Batch Size *Q* (left) and Variance-to-Mean of Demand (right)



4.3.3 Size of the Penalty Costs

VOI also depends on the size of the penalty for mismatches between supply and demand. These costs are reflected in the parameters m_0 and m_1 (the retailer's and supplier's product margin), and the supplier's expediting cost b. As the product margin for either facility decreases, VOI increases. We show this relationship in Table 4.3 (DIS Case) and Table 4.4 (CIS Case) where the values for VOI are averaged across experiments at each level of m_0 and m_1.

Table 4.3: Sensitivity of DIS VOI to Product Margin

Retailer Margin		40%	50%	60%	Mean
Supplier Margin	40%	7.0%	4.8%	3.7%	5.2%
	50%	5.6%	4.0%	3.1%	4.2%
	60%	4.5%	3.3%	2.6%	3.5%
Mean		5.7%	4.0%	3.2%	4.3%

Table 4.4: Sensitivity of CIS VOI to Product Margin

Retailer Margin		40%	50%	60%	Mean
Supplier Margin	40%	12.6%	8.4%	6.0%	9.0%
	50%	11.5%	7.8%	5.5%	8.2%
	60%	11.0%	7.5%	5.3%	7.9%
Mean		11.7%	7.9%	5.6%	8.4%

For the retailer, when the cost of the product is high, the cost of outdating is also high relative to the opportunity cost of a lost sale. Hence, without information sharing, the retailer holds less inventory to avoid excessive outdating. In this scenario, fresher product provided through information sharing reduces the cost of outdating and enables the retailer to achieve a higher service level that enhances revenues for both the retailer and supplier. Conversely, when the cost of the product is low, the cost of outdating is low relative to the opportunity cost of a lost sale. The retailer will consequently have a higher service level without information sharing so that with information sharing, the major benefit is a reduction in the retailer's outdating. In turn, this has a negative impact on the supplier's expected profit. Hence, the opportunity for improving total supply chain profits is greater with a lower retailer margin. The same relationship holds true for the supplier's margin, as lower margins translate into increased holding cost for the supplier.

5. Conclusion

We study the benefits of information sharing in a serial supply chain providing a perishable product. Specifically, we consider a supply chain model consisting of a single product with a fixed lifetime, one supplier, and one retailer that is constrained to order in fixed lot sizes. The value of information is measured as the percent increase in the expected profit of the supply chain over the expected profit achieved without information sharing. The retailer orders according to the results of a Markov Decision Process that balances its holding and spoilage cost with the cost of potential lost sales. The supplier faces uncertainty only in the timing of the retailer's orders, thus it manages this uncertainty using a safety lead-time that balances its holding cost with the cost of expediting orders that cannot be filled through stock on hand. Finally, the information being shared includes the retailer's age dependent inventory state and the retailer's replenishment policy.

We first propose a policy for both supply chain members under no information sharing, and then provide an exact analysis for the expected profits of each firm. We compare these results to the results obtained with information sharing for both a centralized and decentralized supply chain using a numerical experiment. We find that supply chains for perishable products benefit the most from information sharing when

1. Product lifetimes are short and batch order quantities are large.
2. Uncertainty in demand is significant and batch order quantities are large.
3. The supplier faces a high expediting cost or the retailer charges a low margin in relation to the inventory holding cost or cost of spoilage.

The average improvement from information sharing in a centralized supply chain is 8.4%. Comparing the centralized and decentralized cases, we find that information sharing presents a centralized supply chain with an additional average improvement of 95% over a decentralized chain. The benefits of information sharing, however, are not shared equally between the retailer and the supplier. In both cases, the retailer receives the larger average benefit. Moreover, while total supply chain profit always increases with information sharing, either facility may individually realize a decrease in expected profitability. Even in cases when all other parameters are held constant, changing from a centralized to a decentralized supply chain sometimes results in dramatic swings of profitability for the individual firms.

There are a number of important issues still to be addressed. First, we do not model the impact that holding fresher product has on retail sales. As mentioned previously, the availability of perishable products is an order winning criteria of consumers, so it is reasonable to assume that a firm carrying fresher product will observe higher demand and or higher margins than one that carries older product. We expect that the inclusion of this important relationship will only increase the value of information sharing. Second, while we look at information sharing in both a centralized and decentralized setting, it is important to determine the conditions that provide the firms with the incentive to share/use the information in their operating policies. As our numerical test show, an increase in the total supply chain profits is not always pareto improving for both members. Other areas left for future research include arborescent supply chains, longer lead times, different issuing policies, non-stationary demand, and replenishment restrictions on the supplier.

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