Production Control Policies in Supply Chains with Selective-Information Sharing

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We consider a supply chain consisting of one manufacturer (capacitated supplier) and two retailers. We characterize the manufacturer’s optimal production policy under selective-information sharing, in which the manufacturer receives demand and inventory information from only one of the two retailers. We show that the manufacturer’s optimal production policy is a state-dependent base-stock policy and that the base-stock levels have a monotonic structure. We also perform an extensive numerical study to examine how system factors affect the benefit of information sharing and the relative values of information from each retailer. In addition, we identify cases where the cost saving due to receiving information from only one retailer captures most of the saving that can be obtained when the information is received from both retailers. Finally, we investigate the cost effectiveness of echelon-stock policies in systems with full-information sharing and introduce the “information pooling effect” as well as economies of scale with respect to information sharing.

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1. Introduction

In recent years, there has been much emphasis on using modern technologies such as Electronic Data Interchange (EDI) and the Internet to improve the performance of supply chains. Among many potential areas, information sharing has received broad attention because it can reduce the effect of demand variability and helps the participants in supply chains to reduce their operation costs. Utilizing shared information, businesses can gain a competitive advantage by developing more effective production and inventory management policies, which in turn can result in higher profit and better customer service.

One of the most celebrated implementations of demand information sharing is the Campbell Soup Continuous-Replenishment Program (CRP) (Fisher 1997, Cachon and Fisher 1997). In a traditional EDI ordering system, the retailers use EDI only to expedite the ordering process, but the local demand/inventory information is not shared with other members in the supply chain. In many cases it would take four to six weeks for end-demand information to reach third- or fourth-tier suppliers, and information is often distorted by the time it gets there. The cost associated with this slow propagation of information is often very large. Henriott (1999) presents cases in the automotive industry, where this cost is as much as $1 billion annually.

Campbell’s CRP was a big success because it reduced inventories at retailers’ distribution centers by 50%, while the service rate increased from 98.7% to 99.5% (Cachon and Fisher 1997). As a result, more companies in various industries have started to collaborate with their business partners by using information sharing through EDI, e.g., Walmart’s Retail Link, and Automotive Network eXchange (ANX) in the automotive industry. Furthermore, modern companies extend their coordination across corporate and even national boundaries by means of the Internet and the World Wide Web. In addition to its own successful EDI network and supply chain council, Compaq launched a supplier e-Business project called TaiWeb in 1999 to share its product and procurement plans with its main component suppliers in Taiwan. The most compelling evidence of the movement toward information sharing in supply chains was presented by Forest Research (Henriott 1999). According to their survey, about 75% of Fortune 1000 companies are going to share their inventory and demand forecast information with their partners.

Although sharing information is always beneficial, the degree of cooperation varies from one retailer to another in decentralized supply chains. Manufacturers/suppliers must negotiate with their retailers to convince them to share their information. System integration becomes costlier and more complicated as more participants with different information platforms join in the network of information sharing. On the other hand, the information received from one retailer might be more valuable than the information received from another. Thus, it is very important to quantify the value of information received from each retailer. This helps suppliers recognize which retailers have the most valuable or the least valuable information. Suppliers can utilize this evaluation to find answers to questions such as: (1) How much benefit can the supplier/manufacturer get through receiving inventory information from some but not all of her
downstream retailers? Is it possible that sharing information from only one or some participants will be good enough? (2) If we suppose that the system is planning to share information from only some of the downstream retailers, how do different factors such as retailers’ market shares or order sizes affect the decisions regarding which retailers would be the most beneficial partners? The answers to such questions will help suppliers in circumstances in which either (a) there is a limited budget for the information link, and some retailers are asking for a large discount to share their information, or (b) the information link must start with a pilot run consisting of only some retailers. By recognizing the value of the information from each retailer, suppliers will be in a better position in their negotiations with their retailers.

In this paper, we focus on a two-echelon supply chain with one manufacturer (capacitated supplier) and two retailers. Our first objective is to investigate the manufacturer’s optimal production policy under three different scenarios: (1) selective-information sharing, in which the manufacturer receives information from only one of the retailers; (2) full-information sharing, in which the manufacturer receives instant customer demand and inventory information from both retailers; and (3) no-information sharing, in which the manufacturer does not receive any online information from either retailer but instead utilizes the order history from the retailers to develop its own optimal policies. Because full- and no-information sharing are special cases of selective-information sharing, and thus all our analytical results under selective-information sharing hold for the corresponding full-information or no-information sharing models, the paper presents only the analytical results for selective-information sharing. Detailed results for full- and no-information sharing can be found in Huang and Iravani (2004), the full version of this paper.

Our second objective is to provide some insight as to when selective-information sharing is most beneficial and which retailer has the most valuable information. In addition, we will compare the benefit of information sharing in supply chains before and after a merger, and introduce the “information pooling” effect and economies of scale with respect to information sharing.

2. Literature Review

The literature on information sharing in supply chains has been proliferating recently (see Sahin and Robinson 2002 and Chen 2003 for good reviews). Most of the studies on the effects of information sharing in supply chains are for serial systems (e.g., Clark and Scarf 1960; Chen and Zheng 1994a, b; Chen 1998). Furthermore, the majority of the existing research on information sharing in multi-echelon supply chains assumes an exogenous replenishment-type source with ample stock (i.e., an uncaptacitated supplier).

For capacitated production-inventory systems, most researchers focus on the value of information in one-stage or serial systems. For example, Gavirneni et al. (1999) consider a one-manufacturer, one-retailer supply chain with a periodic-review inventory policy. The manufacturer has limited production capacity per period, and the retailer follows an $(s, S)$ policy. The end-item demand is at least one unit per period. They show that monotonic modified order-up-to policies are optimal, and they compute the optimal order-up-to levels through infinitesimal perturbation analysis (IPA) under different demand distributions. They report that shared information in a system with no transportation lead time can reduce the supplier’s cost by 1% to 35%.

On the other hand, the literature on the optimal policies of multiclient supply chains with information sharing is relatively limited. Most of the papers also assume an uncapacitated outside source for the supplier. Chen and Zheng (1997) propose an echelon-stock $(R, nQ)$ policy in one-warehouse, multiretailer, continuous-review systems. They provide procedures to evaluate the performance of the proposed policy. Graves (1996) investigates a multi-echelon system in which all sites apply an order-up-to policy at fixed replenishment intervals. He shows that this system under the proposed policy is close to optimal.

Cachon and Fisher (2000) consider a periodically reviewed system with one supplier and multiple identical retailers in which all the members use $(R, nQ)$ policies. The supplier has information about all the retailers’ inventory positions. They show how having this information benefits the supplier’s order and allocation decisions. Marklund (2002) proposes a different order policy in which a supplier’s order is triggered by the probability of stock-out after replenishment lead time. The numerical study in the paper indicates that there are cases when considerable savings can be made by using the proposed policy instead of the $(R, nQ)$ policy.

Aviv and Federgruen (1998) study a periodically monitored two-stage supply chain with multiple nonidentical retailers under the vendor managed inventory (VMI) program. To analyze the performance of the VMI program, they also study decentralized systems with and without information sharing. In their VMI and decentralized systems, each retailer uses so-called $(m, \beta)$ policies in which orders are issued every fixed number of periods $m$, raising the inventory to the fixed reorder point vector $\beta$. The supplier’s orders are subject to a fixed limit $c$. They claim that modified base-stock policies are optimal for the supplier in the decentralized systems. Simchi-Levi and Zhao (2003) consider a similar supply chain but with only one retailer to investigate the impact of information-sharing frequency on the supplier’s performance.

All the information-sharing literature on systems with multiple retailers assumes that the information is received either from all retailers or from no retailers. For example, in a similar setting to ours, Gavirneni and Tayur (1998) compare the value of information and the benefit of delayed differentiation in periodic review systems. Furthermore, most literature considers a preset inventory policy for the
supplier with parameters that must be optimized. To the best of our knowledge, no study has yet been done on supply chains in which the supplier receives information from only some but not all of the downstream retailers. This is a critical problem in decentralized supply chains in which the degree of cooperation between some retailers and the supplier (manufacturer) is very low. Just as every business would like to know who its most valuable customers are, the supplier would like to know which retailer’s demand/inventory information is the most beneficial.

In this paper, therefore, we explore this issue by focusing on a supply chain with one manufacturer and two retailers, where the manufacturer receives information from (1) none, (2) both, or (3) one of the retailers. The problem focuses on minimizing the manufacturer’s cost. By characterizing the manufacturer’s optimal production policy, we explore the effects of the manufacturer’s production capacity and cost, as well as of the retailer’s order size on the benefit of information sharing. We also address cases in which sharing information from only one retailer (when properly chosen) can capture a large fraction of the benefit of full-information sharing. Note that because all the partners at the lower stage have a common capacitated manufacturer, our model can also represent a simplified multiproduct make-to-stock production system after delayed differentiation. (See Lee and Tang 1997 and Aviv and Federgruen 2001.)

This paper is organized as follows. In §3, we introduce our one-manufacturer, two-retailer problem. In §4, we study the characteristics of the manufacturer’s optimal production policy when she receives information from only one of the retailers. In §5, we perform a numerical study to gain insight into the effects of parameters such as manufacturer’s production capacity and cost on the value of each retailer’s information and on the selection of information-sharing partners. We also investigate the cost effectiveness of echelon stock policies in systems with full-information sharing and introduce the “information pooling effect” as well as economies of scale with respect to information sharing. Section 6 contains concluding remarks.

3. Problem Description

Consider a supply chain with one manufacturer and two retailers (see Figure 1) in a competitive market. The manufacturer produces items in her production facility and keeps them in her inventory to satisfy the retailers’ orders. There is a convex and nondecreasing holding cost \( h(y) \) \((h(y) < \infty \) for a given \( y \)) per unit time when the manufacturer’s inventory level is \( y \). The manufacturer also has a limited capacity with a production rate of \( \mu \) items per unit time.

The customer demand at retailer \( i \) is independent of the other and follows a Poisson process with rate \( \lambda_i \), \( i = 1, 2 \). The retailers use \((Q_i, R_i)\) policies to manage their inventories \((i = 1, 2)\). That is, when retailer \( i \)’s inventory level reduces to reorder point \( R_i \), an order in the size of \( Q_i \) units is issued to the manufacturer. If the manufacturer has enough inventory on hand, the retailer’s order is filled using the manufacturer’s on-hand inventory. Otherwise, the retailers are able to get the unmet part of the order in some other ways, whereupon the manufacturer incurs a linear shortfall penalty \( p \) per unit. We assume that all this happens during an insignificant transportation lead time, and therefore we let \( R_i = 0 \) \((i = 1, 2)\). Because the transportation lead times only affect the retailers’ reorder points in a decentralized supply chain, it is easy to extend our analysis of the manufacturer’s policies to cases with positive transportation lead times between the manufacturer and the retailers.

The shortfall cost \( p \) has been used in prior literature to model different situations, such as (1) the loss of revenue or goodwill due to the shortfall (Archibald 1997); (2) the cost of purchasing the unmet part from other suppliers, including other strategically allied manufacturers in different geographic areas (Gavirneni et al. 1999, Lee et al. 2000); and (3) the cost of expediting (Dekker et al. 2002, Gavirneni 2002).

Let \( Y_\theta(t) \) be the manufacturer’s inventory level at time \( t \), and \( N_\theta(t) \) be the accumulated shortfalls up to time \( t \) under policy \( \theta \). Also, let \( \alpha \in (0, 1) \) be the discount factor. The objective is to find an optimal control policy \( \theta^* \) that minimizes either the discounted total cost over an infinite horizon:

\[
E \left[ \int_0^\infty e^{-\alpha t} h(Y_\theta(t)) \, dt + p \int_0^\infty e^{-\alpha t} \, dN_\theta(t) \right],
\]

or the average cost over an infinite horizon:

\[
\lim_{T \to \infty} \frac{1}{T} E \left[ \int_0^T h(Y_\theta(t)) \, dt + pN_\theta(T) \right].
\]

Figure 1. A two-echelon supply chain with one manufacturer and two retailers.
Without losing generality, we assume that retailer 1 shares his inventory information with the manufacturer but retailer 2 does not. Because the manufacturer does not have access to retailer 2’s inventory information, her production schedule will depend not only on retailer 1’s inventory level, but also on retailer 2’s last order arrival epoch. To analyze this system, we discretize the time horizon into equal, nonoverlapping infinitesimal intervals $\delta t$, where $\delta t \to 0$.

At the beginning of each interval, the manufacturer reviews all the inventory and order information, including her own on-hand inventory $y$, retailer 1’s on-hand inventory $x_1$, and the time-interval index $t_2$ (in length of $\delta t$) since retailer 2’s last order. Based on this information, the manufacturer decides whether to start/keep on producing or to remain idle. Once the manufacturer decides to produce, the production process is a Poisson process with production rate $\mu$, independent of customer demand and retailers’ orders. Thus, in each period (time interval $\delta t$), the probability that one item is produced is close to $\mu \delta t$. Similarly, a customer demand may occur at retailer 1 during this period, and the probability of having one demand arrival at retailer 1 in each period is close to $\lambda_1 \delta t$ as $\delta t \to 0$.

Retailer 2’s orders might also arrive in this period. Because retailer 2 applies $(Q_2, R_2 = 0)$ inventory policies, his order follows an independent renewal process with Erlang$(Q_2, \lambda_2)$ interarrival times. We let $\delta t$ be small enough so that the following are true:

- The probability that retailer 2 places an order of $Q_2$ units in period $[t_2, t_2 + 1]$ is close to $\psi_2(t_2 \delta t) \delta t$, where $t_2$ is the total number of time intervals (in length of $\delta t$) from retailer 2’s last order, and $\psi_2(t)$ is the hazard function of Erlang$(Q_2, \lambda_2)$.
- The probability that more than one item can be produced during the time interval of length $\delta t$ is almost zero.
- The probability of having more than one order of size $Q_2$ from retailer 2 during an interval of length $\delta t$ is almost zero.

We assume that the manufacturer makes her production/idleness decision at the beginning of a period. If the manufacturer’s action is production and an item is produced in that period, it will be put into stock before the inventory is allocated to meet the retailers’ orders in that period. Based on these assumptions, we can establish an MDP model with state space $\mathcal{S} = \{(y, x_1, t_2) \mid y, x_1, t_2 \in \mathbb{Z}^+, 1 \leq x_1 \leq Q_1\}$, action space $\mathcal{A} = \{\text{production, idleness}\}$, and decision epochs being the beginning of each period.

Let $\eta_{0i}(t_2)$ be the joint probability that during period $[t_2, t_2 + 1]$ (one unit of $\delta t$), $i$ customers arrive at retailer 1 and $j$ orders are issued by retailer 2. As an example, $\eta_{01}(t_2)$ represents the probability that in the period $[t_2, t_2 + 1]$ a customer demand arrives at retailer 1, and retailer 2 does not place any order. Therefore, when $\delta t \to 0$,

$$\eta_{01}(t_2) = \left[1 - \lambda_1 \delta t\right] \left[1 - \psi_2(t_2 \delta t) \delta t\right];$$

$$\eta_{02}(t_2) = \left[\lambda_1 \delta t\right] \left[1 - \psi_2(t_2 \delta t) \delta t\right],$$

and $\eta_{ij}(t_2) = 0$ for all $i, j \geq 2$. Thus, we get $\eta_{00}(t_2) + \eta_{10}(t_2) + \eta_{01}(t_2) + \eta_{11}(t_2) = 1$. The optimality equation for the MDP after time discretization under a total discounted cost criterion is

$$f_a(y, x_1, t_2) = h(y) \delta t + \min \left\{ m_\xi(y, x_1, t_2), (1 - \mu \delta t) m_\xi(y, x_1, t_2) + (\mu \delta t) m_\xi(y + 1, x_1, t_2) \right\}, \quad (1)$$

where $\alpha$ is the discount factor, and $m_\xi(y, x_1, t_2)$ is

$$m_\xi(y, x_1, t_2) = \eta_{00}(t_2) \left( \xi f_a([y - 1, Q_1]^+, x_1 - 1 + 1, Q_1, t_2 + 1) + p[1, Q_1 - y]^+ \right) + \eta_{01}(t_2) \left( \xi f_a([y - Q_2]^+, x_1, 0) + p[Q_2 - y]^+ \right) + \eta_{10}(t_2) \left( \xi f_a(y, x_1, t_2 + 1) \right) + \eta_{11}(t_2) \left( \xi f_a([y - 1, Q_1 - Q_2]^+, x_1 - 1 + 1, Q_1, 0) + p[1, Q_1 + Q_2 - y]^+ \right),$$

with $\xi = e^{-\alpha \delta t}$, and

$$[X]^+ = \begin{cases} X & \text{if } X > 0, \\ 0 & \text{if } X \leq 0, \end{cases}$$

$$1_i = \begin{cases} 1 & \text{when } x_i = 1, \\ 0 & \text{otherwise}. \end{cases}$$

The optimality equation under the long-run average cost criterion is

$$g \delta t + f(y, x_1, t_2) = h(y) \delta t + \min \left\{ m(y, x_1, t_2), (1 - \mu \delta t) m(y, x_1, t_2) + (\mu \delta t) m(y + 1, x_1, t_2) \right\}, \quad (2)$$

where $m(y, x_1, t_2)$ is

$$m(y, x_1, t_2) = \eta_{00}(t_2) \left( f([y - 1, Q_1]^+, x_1 - 1 + 1, Q_1, t_2 + 1) + p[1, Q_1 - y]^+ \right) + \eta_{01}(t_2) \left( f([y - Q_2]^+, x_1, 0) + p[Q_2 - y]^+ \right) + \eta_{10}(t_2) \left( f(y, x_1, t_2 + 1) \right) + \eta_{11}(t_2) \left( f([y - 1, Q_1 - Q_2]^+, x_1 - 1 + 1, Q_1, 0) + p[1, Q_1 + Q_2 - y]^+ \right),$$

and $g$ is the optimal average cost per unit time. We set the optimal policy to be idleness when both idleness and production have the same cost.
We would like to emphasize that time discretization has often been used in the analysis and approximation of the continuous-time Markov decision processes (see Hordijk and Van Der Duyk Schouten 1984, Kushner and Dupuis 2001). Our discrete-time model is an asymptotically correct approximation of the continuous-time model. In Huang and Iravani (2004) it has been shown that the optimal action and the optimal average cost of the discrete-time model converges to that of the continuous-time model as the time interval $\delta t$ becomes smaller (approaches zero). We would also like to emphasize that the discrete-time model is a more attractive model in practice than its corresponding continuous-time model. In the continuous-time model, the realization of system states followed by the decision-making process happens in no time. This is usually not the case in practice. Our discrete-time model, on the other hand, allows a small time interval (i.e., $\delta t$) for reviewing the system state as well as for decision making.

4. Characteristics of the Optimal Production Policy

In this section, we analyze the properties of the optimal production policy under selective-information sharing. We define the first-difference operators of any function $v$ on state space $\mathcal{U}$ as follows:

$$D_1 v(y, x, t) = v(y + 1, x, t) - v(y, x, t).$$

We also define the following second-difference operators:

$$D_{xy} = D_1 D_1, D_{yx} = D_1 D_1, \text{ and } D_{y} = D_1 D_1. \text{ We then have the following lemma. (The proof is straightforward and is therefore omitted.)}$$

**Lemma 1.** Under the discounted-cost criterion, idleness is optimal at state $(y, x, t)$ if and only if $D_1 m(y, x, t) \geq 0$. Production is optimal if and only if $D_1 m(y, x, t) < 0$.

According to Lemma 1, we can find the optimal discounted-cost decision at state $(y, x, t)$ by the sign of $D_1 m(y, x, t)$. Let $T$ be the set of functions defined on $\mathcal{U}$ such that if function $v \in T$, then $v$ satisfies

- **Lower bound:**
  - $V_1 D_1 v(y, x, t) \geq -p \quad \forall y, x, t \in \mathcal{U}$.
- **Convexity in $y$** ($D_{xy} v \geq 0$):
  - $V_2 D_1 v(y + 1, x, t) \geq D_1 v(y, x, t)$, $y \geq 0$.
- **Supermodularity in $y$ and $x_1$ ($D_{xy1} v \geq 0$), and submodularity in $y$ and $t_2$ ($D_{y} v \leq 0$):**
  - $V_3 D_1 v(y, x_1, t_2) \leq D_1 v(y, x_1, t_2)$, $y \neq y' \leq Q_1 - 1$.
  - $V_4 D_1 v(y, x_1, t_2) \leq D_1 v(y, x_1, t_2)$, $t_2 \geq t_2 > 0$.
- **Inventory transfer to retailers:**
  - $V_5 D_1 v(y, Q_1, t_2) \leq D_1 v(y + Q_1, 1, t_2)$ $\forall y, x, t_2 \in \mathcal{U}$.
  - $V_6 D_1 v(y, x, 0) \leq D_1 v(y + Q_2, x, t_2)$ $\forall y, x, t_2 \in \mathcal{U}$.

Property $V_1$ introduces a lower bound for function $D_1 f(y, x, t)$. This condition states that by having one more item in inventory, the manufacturer can reduce her cost by at most $p$. Properties $V_2$–$V_4$ are inequalities that result in the monotonicity of the optimal switching surface (see Figure 2). These conditions express that the cost reduced by having one more item in inventory is nonincreasing in $y$ and $x_1$, but nondecreasing in $t_2$. That is, the greater the on-hand inventory for either the manufacturer or retailer 1, or the shorter the time period from retailer 2’s last order, the less the manufacturer can save by having one more unit of on-hand inventory. Properties $V_5$ and $V_6$ show the relationship between the values of function $D_1 f$ for states before and after an order shipment. Note that $(y + Q_1, 1, t_2)$ and $(y, Q_1, t_2)$ are the two states right before

Figure 2. The optimal switching surface for a supply chain with selective-information sharing when manufacturer has: Left: Ample production capacity ($\mu = 4.0$, $p = 10$); Right: Low production capacity ($\mu = 1.5$, $p = 50$).
and right after an order in the amount of \( Q_1 \) is shipped out of the manufacturer’s inventory. According to V4 and V5, we will have \( D_{ij}f_a(y, Q_1, t_2 + 1) \leq D_{ij}f_a(y + Q_1, 1, t_2) \), which implies that when the manufacturer’s inventory is greater than the size of an order, the cost saving achieved by the manufacturer through having one more item in inventory is greater after the order shipment than before it.

Define two operators \( T_a \) and \( T_v \) on the set of real-value functions defined on \( \mathcal{U} \) by

\[
T_a v(y, x_1, t_2) = h(y)\delta t + \min \left\{ v(y, x_1, t_1), (1 - \mu) v(y, x_1, t_1) + (\mu) v(y + 1, x_1, t_1) \right\}
\]

\[
T_v\omega(y, x_1, t_2) = \eta_{10}(t_2) (\xi \omega((y - 1, Q_1^+), x_1 - 1) + 1, Q_1, t_2 + 1) + p[1, Q_1 - y]^+ + \eta_{10}(t_2) (\xi \omega((y - 2, Q_2^+), x_1 - 1) + 0, p[Q_2 - y]^+ + \eta_{10}(t_2) \xi \omega(y, x_1, t_2 + 1) + \eta_{11}(t_2) (\xi \omega((y - 1, Q_1 - Q_2^+), x_1 - 1 + 1, Q_1, t_2, 0) + p[1, Q_1 + Q_2 - y]^+) \right\}.
\]

(3)

and the composite operator \( T = T_v \circ T_a \). We can rewrite the optimal Equation (1) under the total discounted-cost criterion as

\[
f_a(y, x_1, t_2) = T_a f_a(y, x_1, t_2) = T f_a(y, x_1, t_2).
\]

The following proposition shows that all the properties V1–V6 are preserved under \( T_a \) and \( T_v \) (and hence under the optimal one-stage operator \( T \)).

**Proposition 1.** If \( v, \omega \in T \), then

(a) \( T_a v \in T \).

(b) \( T_v \omega \in T \).

(c) \( f_a \in T \).

(d) There exists a stationary optimal policy for the total discounted-cost and total average-cost criteria. The optimal average-cost policies can be obtained by any limit point of the optimal discount-cost policies as \( \alpha \to 0^+ \).

**Proof.** The proof is long and is therefore presented online in Appendix A available at http://orpubs.informs.org/Pages/collect.html. □

Theorems 1–3 characterize the manufacturer’s optimal production policy. Their proofs are presented in online Appendix A.

**Theorem 1.** The manufacturer’s optimal policy under both the total discounted-cost and the average-cost criteria is a state-dependent base-stock policy.

**Theorem 2.** The manufacturer’s optimal base-stock levels are nondecreasing in the time elapsed from retailer 2’s last order shipment and nonincreasing in retailer 1’s on-hand inventory.

**Theorem 3.** If idleness is optimal at state \((y, x_1, t_2)\), then:

- Regardless of the inventory of retailer 1, idleness is also optimal when the manufacturer’s on-hand inventory and the time since retailer 2’s last order shipment are at least \( y + Q_1 \) and at most \( t_2 \), respectively.
- Regardless of the time from retailer 2’s last order shipment, idleness is also optimal when the manufacturer’s on-hand inventory and retailer 1’s on-hand inventory are at least \( y + Q_2 \) and \( x_1 \), respectively.
- Regardless of the inventory of retailer 1 and the time elapsed from retailer 2’s last order shipment, idleness is also optimal when the manufacturer’s on-hand inventory level is at least \( y + Q_1 + Q_2 \).

Similar results as in Proposition 1 and Theorems 1, 2, and 3 also hold for systems under full- and no-information sharing. That is, state-dependent base-stock policies are still optimal, base-stock levels are monotonic, and the relationships of the optimal controls at the states before and after an order shipment are the same as that under selective-information sharing. For detailed descriptions and proofs of the properties under full- and no-information sharing, see Huang and Iravani (2004).

Figure 2 illustrates the optimal production policy under the average-cost criterion for two examples with \( (\lambda_1, Q_1) = (1, 2, 40), (\lambda_2, Q_2) = (1, 0, 30) \), and \( h = 1 \). In the left side of Figure 2, the production capacity \( \mu = 4.0 \) and \( p = 10 \), while in the right side of Figure 2, \( \mu = 1.5 \) and \( p = 50 \). Figure 2 shows the switching surface that separates the states in which idleness is optimal (above and on the surface) from the states in which production is optimal (below the surface). The left side of Figure 2 is a typical example for the optimal production policies in systems with ample production capacities and not very large shortfall costs. In those systems, the manufacturer can sometimes remain idle even when she has no item in inventory. Furthermore, the manufacturer’s inventory in those systems will not go above \( Q_1 + Q_2 \) (=70 in this example). In the right side of Figure 2, however, is a typical example of the optimal production policies in systems in which the manufacturer does not have enough capacity (\( \mu < \lambda_1 + \lambda_2 \)) and the shortfall cost is relatively large. As the figure shows, under these circumstances, the manufacturer would need to keep producing, even when the retailer’s inventories are full. In these systems, therefore, the manufacturer’s inventory can reach above \( Q_1 + Q_2 \).

Theorem 3 indicates that if idling is optimal at state \((y, x_1, t_2)\), it is also optimal at states \((y + Q_1, x_1', t_2)\), \((y + Q_2, x_1, t_2')\), and \((y + Q_1 + Q_2, x_1', t_2')\), regardless of the values of \( x_1' \) and \( t_2' \). This theorem can be used to find the relationship between the lowest and highest points of the switching surface. From the monotonicity of the
optimal policy, it is clear that the switching surface will have its lowest point $y$ (the minimum value of $y$ on the surface) when $x_1 = Q_1$ and $t_2 = 0$. In other words, $y = \min \{ y \mid \text{idleness is optimal at } (y, Q_1, 0) \}$. On the other hand, if idleness is optimal at state $(y, Q_1, 0)$, then according to Theorem 3, idleness will also be optimal at state $(y + Q_1 + Q_2, x'_1, t'_2)$, regardless of the values of $x'_1$ and $t'_2$. Therefore, according to the optimal policy, the manufacturer’s base-stock level will never exceed $\bar{y}$, where $\bar{y} = y + Q_1 + Q_2$.

In the left side of Figure 2, $y = 0$ and $\bar{y} = Q_1 + Q_2 = 70$, while in the right side of Figure 2, $y = 19$ and $\bar{y} = 89$. Unfortunately, it is not easy to obtain a closed form for calculating $y$ because it depends on several parameters of the supply chain. Nevertheless, $y$ can be obtained by solving the MDP model.

Furthermore, Theorem 3 also reveals states in which the retailers’ inventory information has no value for the manufacturer. For example, if idleness is optimal at state $(y, x_1, t_1)$, then retailer 1’s inventory information has no value for the manufacturer when the manufacturer has at least $y + Q_1$. This is because the optimal decision is idleness regardless of retailer 1’s inventory level. Similar properties also hold for full- and no-information sharing systems because those cases are special cases of systems with selective-information sharing.

Theorems 1, 2, and 3 characterize the structure of the optimal policy. The results of these theorems, along with the monotonicity property of the optimal policy, provide a basis for developing good heuristic policies. In other words, in developing a cost-effective heuristic policy, one should make sure that the structure of the heuristic policy does not violate the above properties.

In §5.1.2, we investigate the performance of the well-known echelon-stock policy as an alternative (heuristic) candidate for the optimal policy under full-information sharing. We will study situations where this well-known policy performs poorly.

5. The Benefits of Information Sharing

In this section, we perform an extensive numerical study to provide further insight into the benefits of information sharing in systems with either full- or selective-information sharing. The objectives of this study are (1) to investigate the effects of manufacturer’s capacity and cost structure on the value of information she receives from both or only one retailer, (2) to explore situations in which the manufacturer can get a large fraction of the benefit of full-information sharing by receiving information from only one retailer, (3) to examine the performance of the well-known echelon-stock policy as an alternative to the optimal policy in our supply chain under full-information sharing, (4) to study how manufacturer’s cost structure and capacity, as well as retailers’ market shares and order sizes, affect the manufacturer’s decisions regarding which retailers would be the most beneficial partner for information sharing, and (5) to introduce the information pooling effect and economies of scale with respect to information in supply chains.

Our numerical study includes more than 400 cases. In the next sections, however, we present only some representative cases to save space (see online Appendix B for detailed information about our numerical study).

We study the benefit of information sharing through the following three different categories: (1) $FS$, the cost saving under full-information sharing; (2) $CS_i$, the cost saving under selective-information sharing with retailer $i$; and (3) $SR_i$, the ratio of $CS_i$ to $FS$ ($i = 1, 2$):

$$FS = \left[ \frac{\text{average cost without information sharing} - \text{average cost with full-information sharing}}{\text{average cost without information sharing}} \right],$$

$$CS_i = \left[ \frac{\text{average cost without information sharing} - \text{average cost if sharing information with retailer } i \text{ only}}{\text{average cost without information sharing}} \right],$$

$$SR_i = \left[ \frac{\text{average cost without information sharing} - \text{average cost if sharing information with retailer } i \text{ only}}{\text{average cost without information sharing} - \text{average cost with full-information sharing}} \right].$$

$SR_i$ is an indicator that shows how much of the total cost saving under full-information sharing can be captured if the manufacturer shares information only with retailer $i$. Our numerical study focuses on the long-run average-cost criterion because it better presents the effects of system parameters on the system performance by omitting the effect of the discount factor.

5.1. Impact of System Factors

In this section, we study the effects of different parameters of the supply chain on the benefit of information sharing. Here we assume that the manufacturer has two retailers with identical characteristics, namely, identical market share ($\lambda_1 = \lambda_2$) and identical order size ($Q_1 = Q_2$). In §5.2, we will investigate the problem of partner selection for information sharing in systems with nonidentical retailers.

5.1.1. Impact of Production Capacity and Shortfall-Holding Cost Ratio. Figure 3 shows the effects of capacity on the benefit of information sharing when the manufacturer receives inventory information from only one of the retailers. The horizontal axes in Figure 3 are the ratio $\mu/\lambda_1 + \lambda_2$. This ratio is an indicator of the manufacturer’s ability to handle the demand.

The left side of Figure 3 shows behavior similar to that shown in Gavirneni et al. (1999) for systems with one retailer, namely, that systems with larger capacity benefit more from information sharing. Figure 3 also shows that when the manufacturer’s capacity is tight, even though more than half of the total benefits can be captured by information obtained from only one retailer, the total potential benefits from both retailers are very small. When capacity is ample, information from one retailer usually provides less than half of the total benefits.
5.1.2. Performance of Echelon-Stock Policies. Echelon-stock policies are very popular in current studies of multi-echelon supply chains, partly because they have a simple structure and are easy to implement. In our full-information sharing setting, the echelon-stock policy translates into the following. The manufacturer’s decision is based on the total system inventory \( y + x_1 + x_2 \). If the total system inventory is less than the preset value \( B \), the manufacturer’s decision is to produce; otherwise, the manufacturer’s decision is to idle. Thus, the switching surface of an echelon-stock policy would be the plane \( y + x_1 + x_2 = B \) in space \((y, x_1, x_2)\). Note that the echelon-stock policy has most of the properties of the optimal policy under full-information sharing, but with a simpler structure.

The simplicity of implementing the echelon-stock policy has motivated us to investigate the cost effectiveness of these policies in our supply chain setting under full-information sharing. We compared the performance of the echelon-stock policy with the optimal policy through the following metric:

\[
\Delta_{\text{ech}} = \frac{[\text{average cost under optimal echelon policy} - \text{average cost under optimal policy}]}{\text{average cost under optimal policy}},
\]

in which the optimal echelon-stock policy refers to the echelon policy with the optimal echelon level \( B^* \) (that results in the minimum cost). We examined 72 cases, which are presented in Tables B.1 and B.2 of online Appendix B. For each case, measure \( \Delta_{\text{ech}} \) shows how much implementing the echelon-stock policy (with its simple structure) instead of the optimal policy increases the manufacturer’s cost.

Based on our numerical experiment, we found that implementing the echelon-stock policy cost on average 15% more than the cost of implementing the optimal policy. We observed that the echelon-stock policy performs close to optimal when the production capacity is tight or the shortfall-holding cost ratio is high. These are the cases where the optimal policy has a structure similar to the one in Figure 2 (right side). However, when the capacity is not tight, the cost under the optimal echelon policy can be up to 85% more than the cost of the optimal policy.

The main reason for the poor performance of the echelon-stock policy in systems with ample capacity is as follows. When capacity is high (compared to demand), the manufacturer can lower her inventory cost by being idle and postponing production for a long time while the retailers’ inventory decreases. When the retailers’ inventory levels reach a certain level, the manufacturer can produce a large number of items (in a relatively short time) and raise her inventory to avoid shortfall costs. However, under the echelon-stock policy, the manufacturer loses the flexibility of postponing production as she must produce an item every time the inventory of any retailer decreases by one. This creates a higher holding cost (compared to the optimal holding cost) for the manufacturer and makes the echelon-stock policy less cost effective than the optimal.

When capacity is tight, even under the optimal policy, the manufacturer does not have the luxury of being idle. Therefore, under both the optimal policy and the echelon-stock policy, the manufacturer is producing most of the time to avoid shortfall costs. Thus, there is not much difference between the cost of the optimal policy and the cost of echelon-stock policies in systems with tight capacities.

5.2. Partner Selection for Information Sharing

In this section, we study our supply chain with nonidentical retailers. We explore the parameters that have the greatest effect on the value of the information of each particular retailer. We assume that the cost of negotiating, establishing, and maintaining the information links is the same, no
matter which retailer is selected. This allows us to provide some important insight into how supply chain parameters such as manufacturer’s capacity or cost structure, as well as retailers’ market share and order sizes, can affect the value of the information from each retailer and the selection of a partner for information sharing.

5.2.1. Retailers with Equal Market Shares. Consider a supply chain with two retailers who have equal market shares (i.e., \( \lambda_1 = \lambda_2 \)). If the retailers’ order sizes are the same, then the retailers are identical, and their information will have the same value. However, when retailers’ order sizes are different, the following questions are of interest: (1) Considering the fact that both retailers have the same market share, does it really matter which retailer is chosen as the partner for information sharing? In other words, how much can the difference in order sizes affect the value of information from each retailer, when both retailers face the same demand rate? (2) If it is found that, say, retailer 1 is the more beneficial partner for information sharing, does any change in the manufacturer’s parameters, such as production capacity or cost structure (i.e., shortfall-holding cost ratio), decrease the relative value of information of retailer 1 and make retailer 2 a favorable partner? If so, how?

We examined 140 cases in our numerical experiment to study the above questions (see Table B.3 of online Appendix B). We observed that when retailers have the same market share but order in different sizes, the difference in the value of their information (i.e., \(|CS_1 - CS_2|\)) can be as high as 19%. This indicates that if the manufacturer decides to share information with only one retailer, choosing the right retailer can save her up to 19%.

We also observed that knowing the retailers’ characteristics, such as their market shares or order size, is not enough to choose the best partner between the two for information sharing. More specifically, we found that changes in manufacturer’s cost structure (i.e., the shortfall-holding cost ratio) can reverse the decision regarding the best partner for information sharing.

Figure 4 demonstrates a representative case among the cases that we studied. In that figure, retailers have the same market share (\( \lambda_1 = \lambda_2 = 1.0 \)), but different order quantities (\( Q_1 = 8 \) and \( Q_2 = 12 \)). Figure 4 shows the cost savings under different shortfall-holding cost ratios \( p/h \) when the production capacity is adequate (\( \mu/(\lambda_1 + \lambda_2) = 2 \)).

As the figure shows, when the shortfall-holding cost ratio is low, the retailer with the smaller order quantity is a better (more beneficial) partner for information sharing. However, as the shortfall-holding cost ratio increases, the value of information from the retailer with the smaller order quantity decreases while the information of the retailer with the larger order quantity becomes more valuable. Consequently, retailer 2 becomes a better partner for information sharing when the manufacturer has a high shortfall-holding cost ratio.

The reason that the value of information of the two retailers changes in different directions is that when the shortfall-holding cost ratio is high, the optimal policy requires higher average inventory levels to avoid high shortfall penalties. Under these circumstances, the saving in holding cost due to utilizing the information of retailer 1 is not much different from the saving in holding cost due to utilizing the information of retailer 2. Therefore, the saving in the shortfall cost becomes the dominant factor. Because the retailer with a larger order size (1) might cause a greater shortfall cost when he orders and (2) has a larger variance in his interarrival times, the manufacturer can save more in the shortfall penalty cost when she has a more accurate estimate of the arrival time of the larger order size.

On the other hand, as the shortfall-holding cost ratio decreases, the holding cost becomes a more important factor in cost reduction, and information that can be used to reduce the holding cost will thus have more value. When \( \lambda_1 = \lambda_2 \), the retailer with the smaller order quantity orders more frequently. Therefore, from the perspective of saving on inventory cost, his inventory information becomes more valuable than that of the retailer who orders less frequently. This is because receiving inventory information from the retailer with more frequent orders gives the manufacturer a better approximation for the retailer’s order arrival times, which in turn helps the manufacturer to reduce her inventory cost while being able to respond effectively to the more frequent orders received from the retailer. This is why the retailer whose order quantity is smaller is a better information partner when the shortfall-holding cost ratio is low.

We have also investigated the effect of capacity on partner selection for retailers with equal market share. We observed that when retailers have the same market shares, the effect of changes in the manufacturer’s production capacity on partner selection is insignificant. In other words, we found that the change in the manufacturer’s production capacity sometimes affects the optimal decision regarding partner selection. However, in these situations the cost difference is very small (less than 1.1%) under...
a reasonable range of capacity-demand ratios \(1 < \mu / (\lambda_1 + \lambda_2) \leq 5\), so the opportunity cost of selecting the nonoptimal partner is not significant. However, as we show in the next section, the effect of capacity on partner selection is significant when retailers have different market shares.

5.2.2. Retailers with Different Market Shares. In this section, we consider the case where retailers 1 and 2 have different market shares \((\lambda_1 \neq \lambda_2)\). For those cases in which the retailers’ order sizes also differ (i.e., \(\lambda_1 \neq \lambda_2\) and \(Q_1 \neq Q_2\)), we were not able to detect any general rule for how to select a partner for selective-information sharing. However, in the case where retailers 1 and 2 have different market shares \((\lambda_1 \neq \lambda_2)\) but the same order size \((Q_1 = Q_2)\), our studies generated more insight into the effects of these variables on partner selection for selective-information sharing. As a result, this section focuses on the latter situation rather than the one in which order sizes differ.

When retailers have different market shares but the same order sizes, our intuition might lead us to the conclusion that the retailer with the larger market share is the more beneficial partner for information sharing. The reason would be that the retailer with the larger market share is the manufacturer’s major customer, and the manufacturer tends to believe that the inventory information from this retailer is more valuable. However, our numerical study shows that this is not always true. After examining more than 170 cases in our numerical study with systems with different market shares (see Table B.4 in online Appendix B), we observed cases where choosing the retailer with the larger market share can result in up to a 10% increase in cost, compared to the case where the retailer with the smaller market share is chosen as a partner for information sharing.

As Figure 5 shows, similar to the case with equal market share, the value of information of retailers changes in opposite directions as either production capacity \(\mu\) or the shortfall-holding cost ratio \(p/h\) changes. Our explanation is as follows. When the manufacturer has low capacity, she will try to keep a higher inventory level most of the time because a low-capacity manufacturer cannot rapidly respond to orders from retailers. The saving in shortfall costs is then the dominant factor in selecting the partner for information sharing. When \(Q_1 = Q_2\), the order interarrival times from the retailer with the smaller market share (smaller \(\lambda_1\)) are larger and have a larger variance. On the other hand, because \(Q_1 = Q_2\), order arrivals from either retailer can result in the same shortfall cost. Therefore, the manufacturer benefits more by knowing the inventory level of the retailer with the larger variance in his order interarrival times—and that is the retailer with the smaller market share. In contrast, when the manufacturer has a large capacity, the reduction in holding costs becomes the dominant factor. This is because the manufacturer now has the ability to reduce her inventory while effectively responding to retailers’ orders. Therefore, the retailer with more frequent orders will be the favorable partner for information sharing, as discussed in previous sections. That retailer is retailer 2, who has the larger market share.

With the similar argument, when \(p/h\) is large, the manufacturer will keep a higher inventory level most of the time so that the shortfall cost becomes the key factor in cost reduction. Thus, the retailer with the larger variance in order interarrival times (i.e., the retailer with the smaller demand rate) would be the better partner for selective-information sharing. In contrast, when \(p/h\) is small, inventory information from the retailer with the larger market share is more beneficial because he orders more frequently.

5.2.3. Economies of Scale of Information. In this section, we use an example to show that larger supply chains have the advantage of economies of scale with respect to the value of information. Table 1 shows eight representative cases chosen from the set of 27 test cases in our numerical study.

Figure 5. Benefit of information sharing with retailers of the same order sizes \((Q_1 = Q_2 = 15)\) but different market shares \((\lambda_1 = 0.5, \lambda_2 = 1.5)\). Left: The effect of production capacity \((p/h = 10)\). Right: The effect of shortfall cost \((\mu / (\lambda_1 + \lambda_2) = 2.5)\).
Consider Cases 1 and 2 in Table 1. Both cases are examples of high-capacity systems in which the manufacturer’s capacity $\mu$ is three times larger than the total demand. However, the supply chain in Case 1 has a market share which is 1/3 of the supply chain in Case 2. As Table 1 shows, although both manufacturers have equivalent capacities (compared with their demands), the manufacturer with the larger market share benefits more from information sharing ($FS$ for Cases 1 and 2). This implies that large supply chains benefit from economies of scale with respect to the benefit of information sharing.

Cases 3–8 also confirm this concept. In Cases 3 and 4, the manufacturers have a tight capacity (i.e., capacity 1.2 times larger than the total demand), while Cases 5–8 have the same capacities as in Cases 1–4, respectively, but with a higher shortfall-holding cost ratio $p/h = 20$. As these cases show, the effect of economies of scale decreases as the manufacturer’s capacity-to-demand ratio decreases, and as the shortfall-holding cost ratio increases. For example, in both Cases 7 and 8, the manufacturers have tight capacities, while the supply chain in Case 8 is three times larger than the supply chain in Case 7. As the table shows, in Cases 7 and 8, the cost saving due to full-information sharing for the larger manufacturer is only 0.91% (≈2.51%−1.60%) more than the cost saving for the smaller manufacturer. On the other hand, if Cases 7 and 8 are compared with Cases 3 and 4, it can be seen that the effect of the economies of scale is larger in Cases 3 and 4 that have a smaller shortfall-holding cost ratio. Table 1 confirms that the effect of economies of scale also holds for supply chains in which the manufacturers receive information from only one of their retailers.

### 5.2.4. Information and Production/Inventory Pooling Effects

Consider the following two supply chains:

**SP1:** Supply chain SP1 consists of retailer 1 and manufacturer (supplier) $X$. The manufacturer has a production rate $\mu_x$. The retailer faces a demand $\lambda_1 = 1$ and orders in quantity $Q_1 = 4$.

**SP2:** Supply chain SP2 consists of retailer 2 and manufacturer (supplier) $Y$. The manufacturer has a production rate $\mu_y$. The retailer faces a demand $\lambda_2 = 2$ and orders in quantity $Q_2 = 8$.

Assuming a shortfall-holding cost ratio $p/h = 20$ for both supply chains, Table 2 shows the value of information and the average cost-per-unit time in supply chains SP1 and SP2 under two different scenarios: (1) $\mu_x = 3.0$ and $\mu_y = 6.0$, representing systems with high production capacity, and (2) $\mu_x = 1.2$ and $\mu_y = 2.4$, representing systems with low production capacity.

Let us now assume that manufacturers $X$ and $Y$ merge and establish a larger supply chain in which there is one manufacturer with production capacity $\mu = \mu_x + \mu_y$ and two retailers. Table 3 depicts the cost for this new system under scenarios (1) and (2).

Comparing Tables 2 and 3, we find two interesting effects: the production/inventory pooling effect and the information pooling effect. Consider the cost of supply chains SP1 and SP2 under no-information sharing, as shown in Table 2. Let us also assume that after the merger, the new manufacturer does not receive any inventory information from either retailer. In scenario (1), the cost saving due to the merger of the two supply chains is $(3.81 + 6.11 − 7.94)/(3.81 + 6.11) = 19.96\%$. This cost saving is due to the production/inventory pooling effect, which is the result of the following changed circumstances: (a) in the merged supply chain, the manufacturer has a faster production rate which allows her to be more flexible and responsive; and (b) the manufacturer’s inventory in the merged supply chain

### Table 1. Economies of scale and benefit of information sharing.

<table>
<thead>
<tr>
<th>#</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\mu$</th>
<th>$Q_1$</th>
<th>$Q_2$</th>
<th>$p/h$</th>
<th>FS (FS)</th>
<th>Cost (CS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>1.0</td>
<td>4.5</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>3.52</td>
<td>2.93</td>
</tr>
<tr>
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<td>1.5</td>
<td>3.0</td>
<td>13.5</td>
<td>6</td>
<td>12</td>
<td>5</td>
<td>8.27</td>
<td>5.85</td>
</tr>
<tr>
<td>3</td>
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<td>1.0</td>
<td>1.8</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>4.00</td>
<td>3.81</td>
</tr>
<tr>
<td>4</td>
<td>1.5</td>
<td>3.0</td>
<td>5.4</td>
<td>6</td>
<td>12</td>
<td>5</td>
<td>9.58</td>
<td>8.90</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
<td>1.0</td>
<td>4.5</td>
<td>2</td>
<td>4</td>
<td>20</td>
<td>4.80</td>
<td>4.22</td>
</tr>
<tr>
<td>6</td>
<td>1.5</td>
<td>3.0</td>
<td>13.5</td>
<td>6</td>
<td>12</td>
<td>20</td>
<td>10.65</td>
<td>7.87</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
<td>1.0</td>
<td>1.8</td>
<td>2</td>
<td>4</td>
<td>20</td>
<td>6.91</td>
<td>6.80</td>
</tr>
<tr>
<td>8</td>
<td>1.5</td>
<td>3.0</td>
<td>5.4</td>
<td>6</td>
<td>12</td>
<td>20</td>
<td>13.89</td>
<td>13.54</td>
</tr>
</tbody>
</table>

### Table 2. The benefit of information sharing in supply chains SP1 and SP2.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$\lambda_1$</th>
<th>$\mu_x$</th>
<th>$Q_1$</th>
<th>No-inf.</th>
<th>Full-inf.</th>
<th>FS (FS)</th>
<th>Cost (CS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>1.0</td>
<td>3.0</td>
<td>4</td>
<td>3.81</td>
<td>3.67</td>
<td>3.69%</td>
<td>5.30</td>
</tr>
<tr>
<td>(2)</td>
<td>1.0</td>
<td>1.2</td>
<td>4</td>
<td>5.82</td>
<td>5.74</td>
<td>1.48%</td>
<td>8.84</td>
</tr>
</tbody>
</table>
is, on average, lower than the summation of the manufacturers’ inventories in SP1 and SP2. These two changes result in a saving in the total cost.

Now, suppose that before the merger, both manufacturer $X$ and $Y$ received inventory information from their retailers. Let us now also assume a different post-merger scenario such that the new manufacturer in the merged supply chain will still receive inventory information from both retailers. Under these circumstances, the cost saving due to the merger will be $(3.67 + 5.30 - 6.24)/(3.67 + 5.30) = 30.43\%$ in scenario (1). This saving is $10.47\%$ more than in the case without information sharing! This is because the merged supply chain benefits not only from the production/inventory pooling effect, but also from a similar phenomenon that we call the information pooling effect. That is, the value of the aggregated information of retailers 1 and 2 becomes more beneficial in the merged supply chain than the summation of their values when they are used separately. Our explanation is that the integrated information in the merged supply chain intensifies the effects of the pooled capacity; as a result, the merged supply chain can efficiently utilize the integrated information to better manage its pooled production/inventory. Comparing scenarios (1) and (2), Table 3 reveals that effects of the information (and production/inventory) pooling effect increase as production capacity increases.

The above examples emphasize the fact that supply chains with information sharing can benefit more from a merger than supply chains without information sharing. For example, in scenario (1), $34.4\%$ ($=10.47\%/30.43\%$) of the benefit of the merger is the result of the information pooling effect. Thus, the managers should explore the benefit of the information pooling effect when they evaluate the possibility of a merger with other supply chains. This is because a merger which is not beneficial under no-information sharing may become beneficial if the merged system operates under full-information sharing.

### 6. Conclusion

In this paper, we have studied the benefit of information sharing in a supply chain with one manufacturer and two retailers under selective-information sharing, where the manufacturer receives online information from only one of the retailers. We showed that the manufacturer’s optimal production policy is a state-dependent base-stock policy. We also showed how the optimal base-stock levels change based on the order and inventory information of the retailers.

After conducting an extensive numerical study, we observed the following:

1. Under full-information sharing from identical retailers, the benefit of information sharing in the supply chain can increase up to $42.68\%$. Under selective-information sharing, this benefit is $20.09\%$. Furthermore, under selective-information sharing, the value of information of only one of the two identical retailers can be less or more than $50\%$ of the total value of information of both retailers under full-information sharing. Manufacturers with tight production capacity or very high shortfall-holding cost ratios can capture most of the benefit of full-information sharing through selective-information sharing. On the other hand, when production capacity is relatively high or the shortfall cost is relatively low, selective-information sharing may provide less than half of the benefit provided under full-information sharing.

2. Choosing the best retailer for selective-information sharing depends not only on the retailers’ characteristics (such as order sizes and market shares), but also on the manufacturer’s parameters (such as production capacity and costs). Thus, even if the retailers’ characteristics are not changed, any change in the manufacturer’s production capacity can change the decision as to who will be the most beneficial partner under selective-information sharing.

3. When two manufacturers in two supply chains with information sharing merge, the new supply chain benefits not only from the production/inventory pooling effect but also from the information pooling effect. That is, the combined information of retailers 1 and 2 becomes more beneficial than the sum of the prior values of information of each retailer. This implies that two supply chains that already have information sharing would benefit more from a merger than would two supply chains without information sharing. In addition, the value of information follows the concept of economies of scale. More specifically, large supply chains benefit more from information sharing than smaller supply chains do.

4. In systems under full-information sharing, the popular echelon-stock policy performs very poorly when production capacity is ample and the shortfall-holding cost ratio is not very high. Under these circumstances, the manufacturer’s cost when an echelon-stock policy is implemented can be up to $85\%$ higher than her cost under the optimal policy.

### Table 3. The benefit of information sharing in the merged supply chain.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\mu$</th>
<th>$Q_1$</th>
<th>$Q_2$</th>
<th>Average cost per unit time</th>
<th>Share with R1</th>
<th>Share with R2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td><strong>No-inf.</strong></td>
<td><strong>Full-inf.</strong></td>
<td><strong>FS</strong></td>
</tr>
<tr>
<td>(1)</td>
<td>1.0</td>
<td>2.0</td>
<td>9.0</td>
<td>4</td>
<td>8</td>
<td>7.94</td>
<td>6.24</td>
<td>21.44%</td>
</tr>
<tr>
<td>(2)</td>
<td>1.0</td>
<td>2.0</td>
<td>3.6</td>
<td>4</td>
<td>8</td>
<td>10.60</td>
<td>10.38</td>
<td>2.11%</td>
</tr>
</tbody>
</table>
We conclude this paper by emphasizing the fact that choosing the right partner for selective-information sharing can significantly reduce the manufacturer’s cost. This paper has shed light on how factors such as the manufacturer’s capacity and shortfall-holding cost ratio or retailers’ market shares and order sizes can affect this partner-selection decision. Because the relationship between these factors and the manufacturer’s cost and service levels is very complex, it is not possible to come up with a single, precise, and definite rule for identifying the most beneficial partner for information sharing. Nevertheless, the findings reported in this paper should help managers to better understand the opportunities for selective-information sharing and thus put them in a stronger position in their negotiations about establishing information sharing links.

Appendix

Appendices A and B are available in the online companion at http://or.pubs.informs.org/Pages/collect.html.

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