The Effects of Information Sharing Strategies on Supply Chain Performance

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Abstract—This paper studies the effects of information sharing strategies on supply chain performance. We first consider four common types of information sharing strategies for a supply chain of a single product: (1) order information sharing where every stage of the supply chain only knows the orders from its immediate downstream stage; (2) demand information sharing where every stage has full information about consumer demand; (3) inventory information sharing where each stage shares its inventory levels and demand information with its immediate upstream stage; and (4) shipment information sharing where every stage shares its shipment data with its immediate upstream stage. Our results indicate that information sharing improves supply chain performance of overall inventory cost and fill rate when demand variability is low. We also show that different information sharing strategies affect different performance measures differently and may worsen some performance metrics when demand variability is high. We then find that a hybrid information sharing strategy, which uses the demand information sharing policy in the distribution network while using the inventory information sharing policy in the supplier network, is a better strategy to improve the overall performance of a supply chain of customizable products when the variability of demand mix is high.

*Index Terms*¾ Information sharing, supply chain management, value of information, stochastic demand, product mix variability.

I. INTRODUCTION

More and more companies have recognized that there is a direct link between the performance of supply chains and the availability and quality of timely information. It is widely known that Wal-Mart and Proctor & Gamble (P&G) share information regarding the retail sales of P&G products at Wal-Mart stores. This information enables P&G to do a better job of managing its production of these products and provides Wal-Mart with greater “in store” availabilities. Furthermore, companies such as Dell and Cisco are sharing information with suppliers and customers to reduce working capital and inventories. The flow of information through the supply chain enables them to match supply closely to consumer demand and to anticipate changes in the marketplace. The wide use of advanced information technologies (e.g., EDI and Web technologies) in supply chains also suggests that companies have come to realize the importance of information sharing.

In fact, many supply-chain related problems can be attributed to lack of information sharing between supply chain members. One important observation in supply chain management, prominently known as the bullwhip effect, suggests that demand variability is magnified as it is further upstream in the supply chain. The bullwhip effect is an important concern in supply chain management for several reasons. First of all, the increased order variability requires each supply chain member to hold excessively high inventory levels in order to meet a boom-and-bust demand pattern. Secondly, despite the overall overstocking throughout the supply chain, the lack of synchronization between supply and demand could lead to complete stockout at certain times. Finally, the bullwhip effect increases not only the physical inventories but also the operating costs. Poor demand forecasts based on the distorted orders result in erratic capacity planning and missed production schedule. Therefore, the bullwhip effect should be minimized. Information sharing among supply chain members can provide benefits in terms of supply chain visibility and reduced order variability. For example, sharing of demand information enables each of supply chain partners to forecast accurately based on real demand.

Another important observation is that supply chains with expanding product varieties are faced with increasing uncertainty in demand mix. Many companies have customized their products to satisfy the requirements of different market segments. The demand mix of a customizable product may change widely while the total demand does not change very much. Previous research in supply chain management has mainly concentrated on reducing demand mix uncertainty through delayed product differentiation. In this paper, however, we will show that enhancing the value of information sharing among supply chain members can significantly reduce the uncertainty related to product variety.

The value of information sharing can be defined as the benefits realized from obtaining or sharing information minus the costs associated. The cost of an information sharing policy may include the additional information cost and coordination cost. The information cost may include information systems investment and other charges by either suppliers or customers for providing information, while the coordination cost may include communication costs and administration costs. Recent development in information technologies, such as Web technologies and Enterprise Resource Planning (ERP) systems, dramatically reduce both the information cost and the coordination cost. In this paper we consider the benefits of information sharing and ignore the technology and coordination costs involved.

Recently, academic researchers have showed a growing interest in the value of information sharing in supply chains. Lee, Padmanabhan and Whang [7] found that sharing real demand information across the supply chain members reduces the bullwhip effect. Chen [4] studied the relative benefits of echelon-stock policies over those of installation stock policies in a multi-echelon environment. The latter decisions at a given facility depend only on local inventory information as opposed to this information combined with information on all downstream facilities. Seidmann and Sundararajan [11] treated the level of information sharing not based on its exact content, but rather, based on the impact it has on the parties that contract to share the information. They identified four different levels of information sharing: ordering information, operational information, strategic information, and strategic and competitive information. They investigated how competition and contracting affect the nature of value sharing at each of these levels. Chen et al. [2] quantified the bullwhip effect for multiple-stage supply chains with and without centralized demand information and demonstrated that centralizing demand information can significantly reduce but not completely eliminate the bullwhip effect. Gavirneni, Kapuscinski, and Taylur [5] analyzed information flow between a supplier and a retailer in a two-echelon model of capacitated supply chain. They studied the relationships between capacity, inventory, and information at the supplier level and how these relationships are affected by inventory system and demand distribution. Using a multi-agent simulation model, Tan [13] tested the impact of information sharing on supply chain performance. She studied how various information sharing policies, i.e., no information sharing, sharing of complete demand information, sharing of downstream customer's shipment data, and sharing of downstream customer's inventory information, behave under different supply chain structures and demand patterns. One of her interesting findings is that a hybrid information sharing policy improves supply chain performance under volatile demand. Lee, So, and Tang studied how to use shared information to improve the supplier's order quantity decisions with a known autoregressive demand process [8]. Cachon and Fisher investigated a supply chain model with one supplier, and N retailers, stochastic consumer demand, and batch ordering. They showed analytically how the manufacturer can benefit from using information about the retailer's inventory levels [1].

While the value of information sharing is widely recognized, we want to investigate how information sharing affects supply chain performance, what types of information supply chain members should share, and how they should share it. Information sharing has long been cited as a chief reason for the success of many supply chains, but it also brings to the fore issues of cost, trust, security, and risk. A channel member has to determine not only whether it want to share information with partners but also what types of data it should share, given that its partners may also be working with its competitors. Because information flows are captured by the type of information shared, the study of information sharing based on what its exact content is will lead to a greater understanding of supply chain dynamics.

We study the four common information sharing models in a linear supply chain with N stages: order information sharing (Model 0), demand information sharing (Model 1), inventory information sharing (Model 2), and shipment information sharing (Model 3). In model 0 (Fig. 1), each stage of the supply chain does not know the status of its downstream stages and forecasts are based only on the orders from its immediate downstream stage. The Beer Game is probably the most famous case of Model 0 in a traditional supply chain. Model 1 (Fig. 2) assumes total real demand visibility. Real-time demand information is transmitted from the end-consumer back through every stage in the supply chain. This means that any real change in demand can be known at all points in the supply chain. Direct sales model, sharing of POS data, and collaborative planning and optimization belong to this type of information sharing. Model 2 and 3, where each stage contracts to share its information with only the next supplier up the chain, represents a compromise between the two extremes. In Model 2 (Fig. 3), each stage of the supply chain shares information about its inventory and actual demand with its supplier. This strategy is currently common in the grocery and fashion retailing industry. Vendor managed inventory (VMI), schedule sharing window, and continuous replenishment belong to this type of information sharing. Model 3 (Fig. 4) assumes that each stage knows its downstream customer's shipment data. For instance, in the computer industry, manufacturers, such as HP and IBM, request sell-through data on withdrawn stocks from their resellers' central warehouse. To summarize, these models constitute a range of levels of information sharing: Model 0 is a no information sharing case, Model 1 is a full demand information sharing case, and Model 2 and 3, where each stage looks at the next customer down the supply chain and the next supplier up the supply chain, are one-stage information sharing cases.

We first study how sharing of information about inventory levels, shipments and real demand, affects supply chain performance in a linear supply chain of a single product. We then consider a more realistic supply chain of multiple products and investigate a hybrid information sharing model (Model 4) that combines Model 1 and Model 2 in different parts of a supply chain to improve supply chain performance when demand mix is volatile. The paper makes new contributions in three aspects: It analyzes another supply chain performance metric of fill rate in addition to inventory cost. It investigates the potential of a hybrid information sharing strategy (Model 4) that combines Model 1 and Model 2 in different parts of a supply chain. While previous studies focus on demand quantity variability, this paper introduces product mix uncertainty to the evaluation of information sharing benefits.

The rest of the paper is organized as follows. Section II describes the basic four types of information sharing models and develops managerial insights into these models. Section III proposes the hybrid information sharing strategy and evaluates its effect under product mix uncertainty. Section IV reports a simulation study and investigates its managerial insights. Section V concludes and identifies opportunities for future research.

II. MODELS

Consider a linear supply chain with N stages. For a given stage k, stage k-1 is its customer and stage k+1 is its supplier. The end customer in the supply chain is called the consumer. The end demands, which are independent and identically distributed (i.i.d.) from a normal distribution, arise at stage 1, stage 1 orders from stage 2, etc., and stage N orders from an outside supplier. This triggers material flows in the opposite direction. Each stage has a fixed lead time. Since the assumption of complete information usually made in multi-echelon inventory theory may be unrealistic in real supply chains, this paper treats decentralized environments in which there are multiple decision makers, which may be different firms or different divisions within a single firm. Each stage makes its own decisions based on local information. We assume that each stage maintains a high service level so that each of the N stages can control its inventory "locally." Such an assumption is reasonable when the service level at each stage is very high, 95% or higher. We feel that high service level at each stage is a reasonable assumption as firms, driven by competition, strive to maintain a high customer service. We model the inventory system at each stage as a periodic review, order-up-to system with a fixed review time, one period. Within each period, for a given stage k, the following sequence of events occurs: (1) Demand is forecasted, the inventory decision is made with a target inventory level, and an order is placed to its supplier; (2) demand is realized and outbound shipments are released; (3) inbound shipments are received and inventory cost and fill rate are assessed. We assume that each stage uses the typical moving average forecasting method. When the demand in a period exceeds the on-hand inventory, the excess is backordered. The objective is to find out how information sharing affects the performance of the supply chain.

We make use of two subscripts and one superscript in the model. The first subscript refers to the echelon, the second to the time epoch and the superscript to the model number. Thus X_{kt}^{1} will be the value of variable X at stage k in period t in Model 1. For stationary parameters, we omit the time period. For each stage and period, define:

L = lead time plus 1 (review period),

h = unit holding cost rate,

D = real consumer demand with a mean of μ and a variance of σ^2,

S = the estimated target inventory level,

Q = the quantity of stock ordered,

$\hat{\mu}$ = forecast demand,

$\hat{\sigma}$ = standard deviation of errors of forecasts,

$\boldsymbol{b}$ = average fill rate.

With the above assumptions, the demands seen by each upstream stage are normally distributed. For simplicity, we shall restrict our attention to the case in which the service levels for different stages are the same. But the same approach can be easily adapted to the case in which the service levels are different for different stages. Let μ_k and σ_k, respectively, be the mean and standard deviation of the demand faced by stage k. Safety stocks can be based on either service considerations or a common time supply. Based on service considerations, the expected safety stock at stage k is equal to $z\sqrt{L_k}\ \sigma_k$, where z is the safety-stock factor associated with the customer service level and is fixed for each of the N stages [10]; based on the use of a common time supply, the expected safety stock at stage k, can be expressed in units of the expected demand. In practice, many companies use policies of this form. For instance, a retailer facing an order lead time of three weeks may choose to keep its target inventory level equal to four weeks of forecast demand, with the extra week of inventory representing its safety stock. For a given stage k, we define SS_k as the expected common factor that satisfies

$$z\sqrt{L_k}\ \sigma_k = SS_k\, \mu_k\,. \tag{1}$$

A periodic inventory policy requires each stage of the supply chain to raise its inventory level up to a given target level in each period. One common form of this policy is to set the approximately optimal target inventory level at stage k in period t, S_{kt}, as given by [6]:

$$S_{kt} = L_k\, \hat{\mu}_{kt} + z\sqrt{L_k}\ \hat{\sigma}_{kt}\,, \tag{2}$$

where L_k is the lead time plus 1, $\hat{\mu}_{kt}$ is an estimate of μ_k and $\hat{\sigma}_{kt}$ is an estimate of σ_k. This paper, however, uses a simplified order-up-to policy where the target inventory level is of the form:

$$S_{kt} = (L_k + SS_k)\ \hat{\mu}_{kt}\,, \tag{3}$$

where SS_k is the common safety factor defined by (1).

Note that (2) is similar to (3) with the safety stock $z\sqrt{L_k}\,\hat{\sigma}_{kt}$ replaced by $SS_k\,\hat{\mu}_{kt}$, i.e., the safety stock is expressed in units of the forecasted average demand rather than the forecasted standard deviation of the forecast errors over the lead time.

We use the following performance measurements to evaluate the information sharing models:

Inventory cost. Inventory is the key driver to the supply chain cost. Let μ_k and σ_k, respectively, be the mean and standard deviation of the demand faced by stage k. The average inventory level per period is the sum of safety and average cycle stock, and is given by $z\sqrt{L_k}\,\sigma_k + \mu_k/2$. The average on-order inventory is $L_k\mu_k$. Since we assume complete backordering, and hence no demand is lost in the system, so μ_k is equal to μ. For simplicity, we shall assume that the inventories are valued as the same as the output of each stage. The approximation formula for the total supply chain inventory cost per period is given by

$$\sum_{k=1}^{N} h_k\left(L_k\mu + \mu/2 + z\sigma_k\sqrt{L_k}\right). \tag{4}$$

Fill rate. The fill rate measures the proportion of demands that are met from the inventory on hand. We use the average fill rate across all stages as an important indicator of service level. This is reasonable especially when management is concerned about stockout at each stage. The long-run relationship between the safety-stock factor and fill rate is $\beta_k = 1 - \sqrt{L_k}\,\sigma_k\,G_u(z)/\mu$, where $G_u(z)$ is the standardized loss function [12]. The approximation expression for the average fill rate over all stages can be expressed as

$$\frac{1}{N}\sum_{k=1}^{N}\left(1 - G_u(z)\sigma_k\sqrt{L_k}/\mu\right). \tag{5}$$

Note that equation (4) and (5) are approximations. To simplify our models and focus on analyzing the managerial implications of different types of information sharing, we choose to use the above approximations instead of the exact inventory and fill rate expressions. As shown in equation (4) and (5), for a fixed service level, lower order variance allows each stage to carry less safety stock on average and thus reduces the total inventory cost; for a fixed service level, lower order variance increases the overall fill rate. Hence the performance of the supply chain squarely relies on demand uncertainty seen by each stage. Inventories are often used to protect the supply chain from uncertainties, but it is an expensive solution. We will demonstrate how information sharing can reduce order uncertainty at each stage of the supply chain and hence improve the performance of the supply chain. For this purpose, we study the four common types of information sharing in the following sections.

A. Model 0 -- Order Information Sharing

In Model 0 (see Chen et al [2]), demand forecasts at each stage of the supply chain are based only on local 'demand' information, i.e., the orders from its immediate downstream stage. We assume that each stage uses the simple moving average forecast method with n observations to estimate the mean of demand, i.e.,

$$\hat{\mu}_{1t} = \sum_{i=1}^{n} D_{t-i} \Big/ n ,$$

and

$$\hat{\mu}_{kt} = \sum_{i=1}^{n} Q_{k-1,t-i} \Big/ n , \qquad k = 2, \ldots, N, \tag{6}$$

where $Q_{k-1,t-i}$ is the order placed by stage k-1 in period t-i.

Since demand by nature is random and uncertain, there does not exist an optimal forecasting technique that accurately predicts the market demand. The moving average used in the paper is a most typical forecasting method.

Suppose that each stage, k, follows a period review policy where the target inventory level is given by (3) and the safety stock, SS_k, is chosen to buffer against the order variability from stage

k-1. At stage k, we can determine the variance of Q_{kt} relative to the variance of its demand, $Q_{k-1,t}$. So we write Q_{kt} as

$$Q_{kt} = S_{kt} - (S_{k,t-1} - Q_{k-1,t-1}).$$

Note that Q_{kt} may be negative, in which case we assume that the excess inventory is returned without cost. Using (3) and (6), we can write the order quantity Q_{kt} as

$$\begin{aligned} Q_{kt} &= (L_k + SS_k)\,\hat{\imath}_{kt} - (L_k + SS_k)\,\hat{\imath}_{k,t-1} + Q_{k-1,t-1} \\ &= (1 + (L_k + SS_k)/n)\; Q_{k-1,t-1} - ((L_k + SS_k)/n)\; Q_{k-1,t-n-1}. \end{aligned}$$

The demands seen by stage k are assumed to be independent across periods. Taking the variance of Q_{kt}, we get

$$Var(Q_k) = \left[1 + 2(L_k + SS_k)/n + 2(L_k + SS_k)^2/n^2\right] Var(Q_{k-1}). \tag{7}$$

Hence we can deductively derive the following expression for the variance of the orders placed by stage k for Model 0, Q_k^0, relative to the variance of real demand

$$Var(Q_k^0) = \left\{ \prod_{j=1}^{k} \left[1 + 2(L_j + SS_j)/n + 2(L_j + SS_j)^2/n^2\right] \right\} Var(D), \qquad k = 1, \ldots, N. \tag{8}$$

Note that the above results are similar to these of [3] except that their equations are lower bounds since they zero-off the safety stocks at each stage while our analysis considers the safety stocks.

The increase in demand variability is an increasing function of L_k, the lead times, and SS_k, the safety stocks, and a decreasing function of n, the number of observations used in demand forecasting. The safety stock at each stage also contributes to the increase in order variability. More importantly, the variance increases multiplicatively at each stage of the supply chain.

Empirical evidence also shows that the orders placed by a retailer tend to be more variable than the consumer demand seen by that retailer. This conclusion does not depend on a specific forecasting technique [2].

Let IC^0 be the total inventory cost associated with Model 0. It follows from (3) that IC^0 can be expressed as:

$$IC^0 = \sum_{k=1}^{N} h_k \left(L_k \mu + \mu / 2 + z\sqrt{Var(Q_{k-1}^0)}\sqrt{L_k} \right). \tag{9}$$

Let FR^0 be the overall fill rate of this model. It follows from (4) that FR^0 can be expressed as:

$$FR^0 = \frac{1}{N}\sum_{k=1}^{N}\left(1 - G_u(z)\sqrt{L_k}\sqrt{Var(Q_{k-1}^0)} \Big/ \mu \right) \tag{10}$$

According to (9) and (10), the increased demand variability requires each stage to increase its safety stock in order to maintain a given service level and consequently increases the total inventory cost. It also decreases the fill rates at the upstream stages and thus decreases the overall fill rate of the supply chain. We use Model 0 as a base case to examine other models.

B. Model 1 -- Demand Information Sharing

On the other extreme, demand information sharing assumes that the first stage (i.e., the retailer) shares its real-time demand information with each of the upstream stages. Since each stage has real demand information, each stage will use the same estimate of the mean demand, i.e.,

$$\hat{\mu}_t = \left(\sum_{i=1}^{n} D_{t-i} \right) \Big/ n, \tag{11}$$

When demand information is shared among stages, an echelon inventory policy is used. For a given stage k, the lead time is the echelon lead time, i.e., the accumulation of the local lead time and all the downstream lead times; the echelon inventory is the inventory position of the subsystem consisting of stage k itself and all its downstream stages. Consider an echelon inventory policy where the target inventory level is given by

$$S_{kt} = \left(\sum_{i=1}^{k} (L_i + SS_i) \right) \hat{r}_t , \quad k = 1, \ldots, N, \tag{12}$$

where the safety stock, SS_i, is chosen to buffer against the end demand uncertainty.

According to (7), (11), and (12), we have the following expression for the variance of the orders placed by stage k, Q_k^1, relative to the variance of the end demand (see Chen et al [2]).

$$Var(Q_k^1) = \left[1 + 2\sum_{j=1}^{k} \left(L_j + SS_j \right) \Big/ n + 2\left(\sum_{j=1}^{k} \left(L_j + SS_j \right) \right)^2 \Big/ n^2 \right] Var\left(D \right), \quad k=1, \ldots, N. \tag{13}$$

In comparison with (8), (13) demonstrates that the increase in demand variability at each stage of the supply chain is additive instead of multiplicative. Chen et al. [2] showed that if demand information is shared, the increase in variability seen by each stage of the supply chain is the same whether the supply chain follows an echelon inventory policy or not. Hence the demand information sharing policy minimizes both the bullwhip effect and the safety stock.

Theorem 1. *Compared with Model* 0*, sharing of demand information decreases supply chain inventory by reducing the bullwhip effect. However,*
(a) *it may improve supply chain fill rate when the variance of consumer demand is low,*
(b) *it worsens the fill rate when the variance of consumer demand is high.*

Proof. Let IC^1 be the total inventory cost associated with this model. By substituting (8) and (13) into (4), we compute the inventory savings of Model 1 compared with Model 0. It can be shown that:

$$IC^0 - IC^1 = \sum_{k=1}^{N} h_k z\sqrt{L_k}\left(\sqrt{Var(Q_{k-1}^0)} - \sqrt{Var(D)}\right) \tag{14}$$

Since $Var(Q_{k-1}^0) >> Var$(D), the inventory savings are positive. Thus compared with Model 0, Model 1 dramatically reduces supply chain inventory.

When stage k plans its safety stock based on real demand, the safety stock level at stage k is equal to $z\sqrt{L_k}\ \sqrt{Var(D)}$. Stage k, however, has to use the safety stock for satisfying the orders from its downstream, which have the variance of $Var(Q_{k-1}^1)$. Let z^1 be the safety factor associated with Model 1. We have $z\sqrt{L_k}\ \sqrt{Var(D)} = z^1\sqrt{L_k}\ \sqrt{Var(Q_{k-1}^1)}$. Thus, the safety factor in Model 1 is equal to $z^1 = z\sqrt{Var(D)}\big/\sqrt{Var(Q_{k-1}^1)}$. Let FR^1 be the overall fill rate of this model. By substituting (8) and (13) into (5), we can compute the fill rate improvement of Model 1 compared with Model 0. It can be shown that:

$$FR^1 - FR^0 = \frac{1}{N}\sum_{k=1}^{N}\frac{\sqrt{L_k}}{m}\left[G_u(z)\sqrt{Var(Q_{k-1}^0)} - G_u\left(z\sqrt{Var(D)}\big/\sqrt{Var(Q_{k-1}^1)}\right)\sqrt{Var(Q_{k-1}^1)}\right] \tag{15}$$

Under stable demand, $G_u(z)$ and $G_u\left(z\sqrt{Var(D)}\big/\sqrt{Var(Q_{k-1}^1)}\right)$ are close since service level is high and $\sqrt{Var(D)}$ is close to $\sqrt{Var(Q_{k-1}^1)}$. In addition, since $\sqrt{Var(Q_{k-1}^0)} > \sqrt{Var(Q_{k-1}^1)}$, it is likely that $FR^1 > FR^0$. One would think that as consumer demand becomes more volatile, it would be more beneficial to share the demand information at stage 1 with the upstream stages, but it is not the case here. Even if real demand information is shared between stages of the supply chain, as shown in (13), we still see that the increased order variability at every stage of the supply chain because the time lag and the safety stock amplify the variance of demand. When the variability of consumer demand is high and service level is significantly affected, if each stage plans its safety stock based on the consumer demand, which may insufficiently deviate from the orders from its downstream customer, the backlog problem may arise and be aggravated as it moves upstream through the supply chain. Severe backlogs will result in low fill rates. In this case, $\sqrt{Var(Q_{k-1}^1)} > \sqrt{Var(D)}$ leads to $FR^1 < FR^0$, i.e., the overall fill rate could be reduced. The theorem also explains why the optimal echelon inventory policy is vulnerable to high demand variability. By keeping barely the minimum safety stock, each upstream stage cannot be ramped up and down rapidly enough to follow swings in demand. The insight is that when consumer demand variance is high, each stage of the supply chain must keep sufficient inventory buffer to cope with the variability of its demand in order to maintain a certain service level.

C. Model 2 -- Inventory Information Sharing

In this type of information sharing, each stage shares its inventory and demand information with its immediate upstream stage. Suppose stage k-1 shares its actual demand and inventory status with stage k period by period. For any period t, the following are defined for stage k-1 after an order is placed and demand occurs: on-hand inventory $I_{k-1,t}$; backorders, $B_{k-1,t}$; on-order inventory, $OI_{k-1,t}$; inventory position, $IP_{k-1,t} = I_{k-1,t} - B_{k-1,t} + OI_{k-1,t}$; and target inventory level, $S_{k-1,t}$. By knowing these information, stage k can derive the orders to stage k-1, $Q_{k-2,t-1} = S_{k-1,t-1} - IP_{k-1,t}$, and the orders placed by stage k-1, $Q_{k-1,t} = S_{k-1,t} - IP_{k-1,t}$. Two distinct characteristics of this relationship are the following. First, because stage k knows the demand to stage k-1, both stage k and stage k-1 can forecast the mean of demand based on the orders of stage k-2 in n periods.

$$\hat{\mu}_{1t} = \hat{\mu}_{2t} = \sum_{i=1}^{n} D_{t-i} \Big/ n, \quad k = 1, 2, \text{ and}$$

$$\hat{\mu}_{kt} = \hat{\mu}_{k-1,t} = \sum_{i=1}^{n} Q_{k-2,t-i} \Big/ n, \quad k = 3, \ldots, N, \tag{16}$$

where $Q_{k-2,t-i}$ is the order placed by stage k-*2* and received by stage k-1 in period t.

Moreover, stage k can plan its safety stock based on the orders of stage k-1 in order to provide a given customer service level. Therefore, by knowing its downstream inventory information, stage k can implement the 2-stage echelon-based inventory control. Hence we can derive the variance of the orders placed by stage k:

$$Var(Q_k^2) = \left[1 + 2\sum_{j=1}^{k}(L_j + SS_j) \Big/ n + 2\left(\sum_{j=1}^{k}(L_j + SS_j) \right)^2 \Big/ n^2 \right] Var(D), \quad k = 1, 2,$$

and

$$Var(Q_k^2) = \left[1 + 2\sum_{j=1}^{k}(L_j + SS_j) \Big/ n + 2\left(\sum_{j=1}^{k}(L_j + SS_j) \right)^2 \Big/ n^2 \right] Var\left(Q_{k-2}^2\right), \quad k = 3, ..., N, \qquad (17)$$

where the safety stock, SS_j, is based on the variability of the orders from stage $j-1$.

In comparison with (8), (17) demonstrates that the increase in demand variability between stage k and stage k-1 is additive not multiplicative. Stage k uses the orders to stage k-1, which is less variable than the orders placed by stage k-1, to create more accurate forecasts. Thus, Model 2 eliminates one stage of information distortion, i.e., stage k-1, and consequently reduces some degree of the bullwhip effect. Moreover, by monitoring its downstream inventory levels, stage k synchronizes its production and/or delivery schedules with the downstream demand to ensure that products are consistently available to the customer. So each stage can maintain a high service level.

Theorem 2. C*ompared with Model 0, sharing of inventory information not only improves supply chain fill rate but also reduces certain degree of supply chain inventory; compared with Model 1, this policy increases inventory cost when the variability of the end demand is high.*

Proof. Let IC^2 be the total inventory cost associated with Model 2. It follows from (4), (8) and (17) that the inventory savings associated with Model 2 compared with Model 0 is given by:

$$IC^0 - IC^2 = \sum_{k=1}^{N} h_k z \sqrt{L_k} \left(\sqrt{Var(Q_{k-1}^0)} - \sqrt{Var(Q_{k-1}^2)} \right) \qquad (18)$$

Let FR^2 be the overall fill rate of Model 2. It follows from (5), (8) and (17) that the fill rate improvement compared with Model 0 can be expressed as:

$$FR^2 - FR^0 = \frac{1}{N}\sum_{k=1}^{N}\frac{\sqrt{L_k}}{m}G_u(z)\left(\sqrt{Var(Q_{k-1}^0)} - \sqrt{Var(Q_{k-1}^2)}\right) \tag{19}$$

Since $Var(Q_{k-1}^0) > Var(Q_{k-1}^2)$, we have $IC^2 < IC^0$. In addition, since $Var(Q_{k-1}^0) > Var(Q_{k-1}^2)$, we have $FR^2 > FR^0$.

Comparing (18) with (14), we also have $IC^2 > IC^1$ since $Var(Q_{k-1}^2) > Var(D)$, i.e., the inventory savings of Model 2 is less than that of Model 1. As consumer demand is getting volatile, $Var(Q_{k-2}^2)$ is getting larger than $Var(D)$ and the safety stock at stage k is getting larger correspondingly.

D. Model 3 -- Shipment Information Sharing

In Model 3, each stage of the supply chain knows its downstream customer's outbound shipment data. A shipment represents the amount of a product each stage immediately ships to its customer in response to a customer order after previous backorders are met. Suppose stage k-1 shares its shipment data with stage k. Let $W_{k-1,t}$ and $I_{k-1,t}$, respectively, be stage k-1's outbound shipment and on-hand inventory in period t. We have $W_{k-1,t} = \min\{I_{k-1,t}, Q_{k-2,t}\}$. If each stage maintains a high fill rate, the downstream shipments are very close to the orders to the downstream stage. In this case, we can use the variance of downstream shipments to approximate that of the orders to the downstream stage. It follows from (17) that the variance of the orders placed by stage k can be expressed as:

$$Var\left(Q_k^3\right) \approx \left[1 + 2\sum_{j=1}^{k}(L_j + SS_j)\Big/ n + 2\left(\sum_{j=1}^{k}(L_j + SS_j)\right)^2 \Big/ n^2\right] Var\left(W_1^3\right),\ k = 1, 2,$$

and

$$Var\left(Q_k^3\right) \approx \left[1 + 2\sum_{j=1}^{k}(L_j + SS_j)\Big/ n + 2\left(\sum_{j=1}^{k}(L_j + SS_j)\right)^2 \Big/ n^2\right] Var\left(W_{k-1}^3\right), \quad k = 3, \ldots, N, \tag{20}$$

where the safety stock, SS_j, is based on the variability of the shipments of stage j-1.

Like Model 2, this model eliminates one stage of distortion since the shipment data, unlike the downstream orders, are not subject to the bullwhip distortion. However, when stock-outs occur at the downstream, the outbound shipments under-represent the demand to the downstream stage and consequently underestimate the safety stock needed to buffer against demand uncertainty. In the long run, the mean of the shipments of stage k-1 can be expressed by the product of the mean of the expected demand i and the fill rate $\boldsymbol{b}_{k\text{-}1}$. Thus, planned on the downstream shipments, the expected target inventory at stage k is given by:

$$S_k^3 = E\left(S_{kt}^3\right) = (L_k + SS_k)\, \boldsymbol{b}_{k\text{-}1}\, E\left(\grave{\imath}_{\,k-1,t}\right) = (L_k + SS_k)\, \boldsymbol{b}_{k\text{-}1}\, \boldsymbol{m}, \tag{21}$$

Therefore, the safety stock for S_k^3 is equal to $\left(L_k + SS_k\right)\boldsymbol{b}_{k-1}\boldsymbol{m} - L_k\boldsymbol{m}$ $= \left[\hat{a}_{k-1} - (1 - \hat{a}_{k-1})\, L_k / SS_k\right] SS_k\ i$. If the safety stock level $SS_k\, i$ in the expected target inventory level S_k = $(L_k + SS_k)\, i$ gives a safety factor of z, it follows from (1) that S_k^3 gives a safety factor of $\left[\hat{a}_{k-1} - (1 - \hat{a}_{k-1})\, L_k / SS_k\right] z$. Hence, compared with Model 2, this model decreases service level and consequently stock-outs increase and fill rates decrease.

Theorem 3. *Compared with model 0, if each stage of the supply chain has a really high customer service level, sharing of one-stage shipment data reduces supply chain inventory while maintaining a stable fill rate. Otherwise, it may underestimate the safety stock to buffer against the demand uncertainty and result in a low fill rate under unstable demand.*

Proof. Let IC^3 be the total inventory cost associated with Model 3. It follows from (3), (7) and (19) that the inventory savings associated with Model 3 compared with Model 0 is given by:

$$IC^0 - IC^3 = \sum_{k=1}^{N} h_k z \sqrt{L_k}\left(\sqrt{Var(Q_{k-1}^0)} - \sqrt{Var(W_{k-1}^3)}\right) \tag{22}$$

Let FR^3 be the overall fill rate of Model 3. Since planning inventory based on the shipments of stage k-1 gives the safety factor of $[\hat{a}_{k-1} - (1-\hat{a}_{k-1})\, L_k / SS_k]z$, similar to (14), it follows from (4), (7) and (19) that the fill rate improvement compared with Model 0 can be expressed as:

$$FR^3 - FR^0 = \frac{1}{N}\sum_{k=1}^{N}\frac{\sqrt{L_k}}{m}\left\{G_u(z)\sqrt{Var(Q_{k-1}^0)} - G_u\left[z\left(\hat{a}_{k-1} - (1-\hat{a}_{k-1})\frac{L_k}{SS_k}\right)\frac{\sqrt{Var(W_{k-1}^3)}}{\sqrt{Var(Q_{k-1}^3)}}\right]\sqrt{Var(Q_{k-1}^3)}\right\} \tag{23}$$

Since $Var(Q_{k-1}^0)$ > $Var(Q_{k-1}^3)$ > $Var(W_{k-1}^3)$, the inventory savings are positive. Since $[\hat{a}_{k-1} - (1-\hat{a}_{k-1})(L_k / SS_k)]$ is getting much less than 1 when the fill rate b_{k-1} is low, the fill rate change may be negative. Many companies are currently using a product's historical shipment (or sales) data to forecast the customer demand. If a company services its customer extremely well and has 100% service level, there will be virtually no difference between shipments and true demand. However, if a company is frequently short of product or late in fulfilling orders, there may be a significance difference between what was shipped and what the customer demanded. In this case, using shipments to forecast demand results in a low fill rate and a high backorder. This model is also more sensitive to the variability of consumer demand since b_{k-1} is decreasing with the variability of consumer demand.

A simple method to adjust the downstream shipments to better reflect the customer's true demand is that each stage tries to capture information on backorders (also including lost sales) and share this information with its supplier. Suppose stage k knows stage k –1's shipments and backorders. It can estimate stage k –1's real demand by adding its backorders to its shipments. Let $B_{k-1,t}$ be stage k –1's backorder in period t. We have

$$Q_{k-2,t} = W_{k-1,t} + B_{k-1,t} \tag{24}$$

With this equation, each stage of the supply chain can derive the demand to the downstream stage from its historical shipments and backorders data.

III. SUPPLY CHAIN of CUSTOMIZABLE PRODUCTS

In Section II, we have studied the four basic information sharing models in the context of a simple linear supply chain that carries a single product. In practice, many companies have mass-customized their products to meet the requirements of different markets. The demand mix of a customizable product may change widely while the total demand does not change very much. Thus supply chains that carry customizable products are faced with increasing uncertainty in product mix. Given a realistic supply chain that carries multiple products, how should we use these information sharing strategies? We have already seen that the value of information sharing relies heavily on demand patterns. While the demand information sharing policy lowers the inventory in the supply chain, the reduced inventory gives the supply chain less buffer to cope with a sudden increase in consumer demand. The inventory information sharing policy, on the other hand, gives the best customer service, but both the bullwhip effect and the high product availability may drive the inventory up when demand is highly volatile. Hence the value of information sharing depends on demand patterns. Moreover, each different part of the supply chain may have its own distinct characteristics and may require a different information sharing strategy. In this section, we propose a hybrid information sharing strategy, which takes advantage of the strengths of both demand information sharing and inventory information sharing, for managing a supply chain with volatile demand mix.

Our primary motivation in developing the hybrid information sharing strategy comes from our experience at a major electronics manufacturer that manufactures radio products. One of the goals of the manufacturer is to control inventories in its distribution network through enhancing the value of information and to provide insights for its global supply chain, which consists of local and offshore suppliers, factories, super distribution centers (DCs), regional DCs and dealers. These facilities are distributed all over the world. By moving to a more systems-integrated environment, the company adopted schedule sharing window to schedule factories based on product usage and inventory level information supplied by the downstream stages at the supply chain. But the problem is that DCs strive to maintain a high customer service level by setting very large windows and dealers do not want to carry inventories and want immediate deliveries. Hence the company carries several months of inventory at its DCs.

The problem with the manufacturer is a mismatch between the schedule sharing strategy and its supply chain. The radio product is a customizable product that provides more than one hundred localized versions of a basically similar product to satisfy the requirements of different markets. Its demand has high product mix variability. The manufacturer needs a more effective information sharing policy to coordinate its supply chain. This section will show that a hybrid strategy is an appropriate strategy for this case. Before we get into the model of hybrid information sharing (Model 4), we first discuss the different characteristics throughout the supply chain.

First of all, a typical supply chain can be divided into a supplier network (upstream of final assembly) and a distribution network. Each sub-network has its own distinct characteristics. The supplier network, in which products are in the raw or semi-finished states and to be transformed and assembled at the manufacturer, is further away from consumers. Its inventories, including parts, components and sub-assemblies, have less value, greater commonality, and greater flexibility than finished products. Partnerships between suppliers and final assembly are important since a better knowledge of the supplier production schedules and part availability is of high value to the manufacturer in order to get the supplies in time for production. As different input factors are complementary, one part's shortage will halt the entire production line. So the objective of the supplier network is to improve availability and responsiveness to the manufacturer.

On the other hand, the distribution network is close to consumers. Finished products have a much higher value, greater differentiation, and less flexibility than components. High inventory cost rates and high demand uncertainty require both the manufacturer and distributors to better forecast demands based on real demand. So the objective of the distribution network is to convey the right demand and lower inventories through reducing the bullwhip effect.

Therefore, the supplier network and the distribution network require different information sharing strategies. In a volatile market place, the inventory information sharing policy may be good for the supplier network because it offers the best customer service. The demand information sharing policy, on the other hand, may be good for the distribution network because it provides each stage with real demand information and reduces the bullwhip effect. Matching the information sharing strategy with supply chain positions can improve overall supply chain performance.

Secondly, demand patterns can play an important role in determining information sharing strategies. In a volatile market, demand may change in demand volume, product mix, or both. Based on demand patterns, a product falls into one of three categories: functional product, customizable product, or innovative product. Functional products, like shampoo for dry, normal and oily hair, meet people's basic needs and have stable demand patterns, long life cycles and low product differentiation. Customizable products may have an overall stable demand but unpredictable mix to satisfy individual needs, such as pagers with thousands of customizable features. Finally, innovative products, such as fashion apparel, have unpredictable demand volume and mix, short product life cycles, and long production lead times. The challenge thus is to introduce new products to the right emerging markets and to exit the shrinking markets at the right time. In today's increasingly complex business environment, supply chains that supply customizable and innovative products are faced with increasing uncertainty in product mix. Under volatile product mix, using the demand information sharing policy alone may give low fill rates at upstream stages, while using the inventory information sharing policy alone may drive inventory up. Therefore, we need to devise an effective hybrid strategy to cope with product mix uncertainty.

In summary, supply chain structure and demand patterns determine what type of information sharing models should be used. One may obtain the better results by applying these strategies in combinations. As indicated above, one of promising combinations is a hybrid strategy that uses the demand information sharing policy in the distribution network and the inventory information sharing policy in the supplier network.

A. Model 4 -- Hybrid Information Sharing

Let's see how the hybrid information sharing model works where demand information sharing is used in the distribution network and inventory information sharing is used in the supplier networks. Consider a supply chain that supplies M end-products that all share the same design platform (Figure 5). Each of them requires processes performed in N stages. Stages N to k are common operations to produce the common platform for the products. Stage k is the manufacturing stage where product differentiation occurs and products are considered to be "distinct" after it. Let the number in parentheses denote the product. $D_t(i)$ and $Q_{kt}(i)$, respectively, denote the end demand and the order placed by stage k for product i in period t (i = 1,…, M; t = 1, 2, …). For each i = 1, …, M, the variables $\{D_t(i)$: t = 1, 2, …} are assumed to be i.i.d with a mean of m_i and a variance of s_i^2. Let $\tilde{n}_{ij}$ denote the coefficient of correlation in demands of products i and j. Let D_t = $\sum_{i=1}^{M} D_t(i)$ denote the aggregate demand in period t which has mean i = $\sum_{i=1}^{M} \grave{i}_i$ and variance $\acute{o}^2 = \sum_{i=1}^{M}\left(\acute{o}_i^2 + \sum_{j=1,\, j\neq i}^{M} \tilde{n}_{ij}\acute{o}_i\acute{o}_j\right)$. Note that $s \le \sum_{i=1}^{M} \acute{o}_i$ for any r. The demands for different end -products are most likely to be negatively correlated if the total demand does not change much. Therefore, by knowing real demand information, the distinct stages are able to minimize the bullwhip effect while the common stages are able to make good use of the risk-pooling effect.

According to the hybrid strategy, demand information is shared among the distinct stages. Hence the real demand for each product is propagated to stage k, the manufacturing stage, with minimum distortion. At the same time, the common stages see the pooled demand of end-products, which is relatively stable although the demand for each product may vary widely. Therefore, the total demand variance seen by stage k is given by:

$$Var\left(D_k^4\right) = \left[1 + 2\sum_{i=1}^{k-1}(L_i + SS_i)\Big/ n + 2\left(\sum_{i=1}^{k-1}(L_i + SS_i)\right)^2 \Big/ n^2\right] s^2 . \qquad (25)$$

Then we have the following expression for the variance of the orders Q_i^4, placed by a given stage i:

$$Var\left(Q_i^4(l)\right) = \left[1 + 2\sum_{j=1}^{i}(L_j + SS_j)\Big/ n + 2\left(\sum_{j=1}^{i}(L_j + SS_j)\right)^2 \Big/ n^2\right] Var\left(D(l)\right),$$

$$i = 1, \ldots, k\text{-}1,\ l = 1, \ldots, M,$$

where SS_j is chosen to buffer against the end demand variability for product l and

$$Var\left(Q_i^4\right)=\left[1+2\sum_{j=i-1}^{i}(L_j+SS_j)\Big/n+2\left(\sum_{j=i-1}^{i}(L_j+SS_j)\right)^2\Big/n^2\right]Var\left(D_k^4\right),\quad i=k,\, k+1, \text{ and}$$

$$Var\left(Q_i^4\right)=\left[1+2\sum_{j=i-1}^{i}(L_j+SS_j)\Big/n+2\left(\sum_{j=i-1}^{i}(L_j+SS_j)\right)^2\Big/n^2\right]Var\left(Q_{i-2}^4\right),\quad i=k+2,\, \ldots,\, N, \tag{26}$$

where the safety stock, SS_j, is based on the variability of the orders from stage $j-1$.

Let's look at the benefits of Model 4 compared with Model 0. For Model 0, the variance of the aggregate demand at stage k can be expressed as:

$$Var\left(D_k^0\right)=\left\{\prod_{j=1}^{k}\left[1+2(L_j+SS_j)/n+2(L_j+SS_j)^2/n^2\right]\right\}\text{ó}^2$$

Thus, it follows from (8) that the variance of the orders placed by stage i can be expressed as:

$$Var\left(Q_i^0(l)\right)=\left\{\prod_{j=1}^{i}\left[1+2\left(L_j+SS_j\right)/n+2\left(L_j+SS_j\right)^2/n^2\right]\right\}Var\left(D(l)\right),\quad i=1,\ldots,k\text{-}1,\ l=1,\ \ldots,M,$$

and,

$$Var\left(Q_i^0\right)=\left\{\prod_{j=k}^{i}\left[1+2\left(L_j+SS_j\right)/n+2\left(L_j+SS_j\right)^2/n^2\right]\right\}Var\left(D_k^0\right),\quad i=k,\ \ldots,\ N, \tag{27}$$

where SS_k is chosen to buffer against the order variability from stage i-1.

Theorem 4. *When demand mix uncertainty is high in the supply chain of multiple customized products, the hybrid information sharing policy, which uses the demand information sharing policy among the distinct stages of the supply chain and the inventory information sharing policy among the common stages of the supply chain, can significantly reduce inventory while allowing the supply chain to operate at a high fill rate.*

Proof. Let IC^4 be the total inventory cost associated with Model 4. It follows from (4), (26) and (27) that the inventory savings associated with Model 4 compared to Model 0 is given by:

$$IC^0 - IC^4 = \sum_{i=1}^{k-1}\sum_{l=1}^{M} h_i z\sqrt{L_i}\left(\sqrt{Var(Q_{i-1}^0(l))} - \sqrt{Var(Q_{i-1}^4(l))}\right) + \sum_{i=k}^{N} h_i z\sqrt{L_i}\left(\sqrt{Var(Q_{i-1}^0)} - \sqrt{Var(Q_{i-1}^4)}\right). \tag{28}$$

Let FR^4 be the overall fill rate of this model. It follows from (5), (26) and (27) that the fill rate improvement compared with Model 0 can be expressed as:

$$FR^4 - FR^0 = \frac{1}{N}\sum_{i=1}^{k-1}\frac{\sqrt{L_i}}{M}\sum_{l=1}^{M}\left[\frac{G_u(z)}{m_l}\sqrt{Var(Q_{i-1}^0(l))} - G_u\left(\frac{zVar(D(l))}{\sqrt{Var(Q_{i-1}^4(l))}}\right)\frac{\sqrt{Var(Q_{i-1}^4(l))}}{m_l}\right]$$
$$+\ \frac{1}{N}\sum_{i=k}^{N}\frac{\sqrt{L_i}}{m}G_u(z)\left[\sqrt{Var(Q_{i-1}^0)} - \sqrt{Var(Q_{i-1}^4)}\right] \tag{29}$$

From (26) and (27), it is easy to see that $Var(Q_{i-1}^0(l)) > Var(Q_{i-1}^4(l))$ for $i = 1, \ldots, k-1$, $l=1, \ldots, M$, and $Var(Q_{i-1}^0) > Var(Q_{i-1}^4)$ for $i = k, \ldots, N$. It follows (28) and (29) that both the inventory savings and the fill rate improvements over Model 0 are positive. The hybrid information sharing policy performs better than other information sharing policy because it matches the value of information sharing to the supply chain structure and product demand features by taking into account both the risk pooling and bullwhip effect.

IV. SIMULATION RESULTS

Section III has shown that information sharing can reduce the demand variability, which is caused by the information gaps among channel players and the resulting need for the safety stocks in the supply chain. It has also shown that the reduction in demand variability allows the supply chain to operate at high service levels with low inventories. This section reports on several simulation experiments that illustrate the effects of information sharing strategies on supply chain performance.

In our first example, we study the behaviors of the four basic models under low consumer demand variability. Using a multi-agent simulation model, we simulated a linear supply chain with four stages: retailer (tier 1), distributor (tier 2), manufacturer (tier 3) and supplier (tier 4). The end-demand process is specified by ì =10000 and ó =866. The replenishment lead time for each stage is 3 periods. We ran the simulation for 150 periods per run and averaged the statistics over 150 periods. Then we repeated 10 runs and averaged the statistics over ten runs. Using Model 0 as a base case, we defined as the value of information sharing the difference in each model's inventory cost and fill rate over Model 0, i.e., (Model 0 cost–Model *i* cost)/Model 0 cost and (Model *i* fill rate–Model 0 fill rate)/Model 0 fill rate. Fig. 6 reports the simulation estimates of these percentage benefits. The demand information sharing policy experiences 74.75% decrease in inventory and a slight increase in fill rate. The inventory information sharing policy experiences 5.79% increase in fill rate while its inventory savings 34.32% are not as significant as that of the demand information sharing policy. The shipment information sharing policy experiences 52.73% decrease in inventory while there is a drop in fill rate. The pattern depicted in Fig. 6 is consistent with the analytical findings presented in Section II, which can be summarized as follows. When demand is relatively stable, information sharing can significantly reduce information distortion and order variability. The reduction of order variability both reduces inventory and improves fill rate.

In our second example, we study the behaviors of these models under high consumer demand variability. This experiment considers a single product with a demand fluctuating between two processes. The high-range demand is specified by ì =15,000 and ó =1299, the low-range demand is specified by ì =5,000 and ó =433, and the high or low range is randomly selected every simulation cycle. Other parameters are the same as those in example 1. Fig. 7 presents the simulation estimates of the percentage benefits realized through information sharing under volatile demand. Compared with the order information sharing policy, the demand information sharing policy experiences 18.74% decrease in fill rate; the inventory information sharing policy experiences 3.96% increase in fill rate but its inventory savings are less than that of the demand information sharing policy; the shipment information sharing policy experiences 6.32% decrease in fill rate. The pattern depicted in Fig. 7 also is consistent with the findings presented in Section

II, which may be explained as follows. When the variance of consumer demand is high, each stage of the supply chain needs to keep enough safety stock to buffer against high order variability. The demand information sharing policy lowers supply chain inventory by planning its safety stock based on consumer demand, but the resulting lower buffer gives lower fill rate. The inventory information sharing policy, on the other hand, gives the best customer service, but may drive inventory up when consumer demand has high variance. Under the shipment information sharing policy, each stage under-estimates the downstream demand and results in a low fill rate.

Finally, we study the behavior of the hybrid information sharing policy when product mix is volatile. This experiment considers the scenario that four end products are customized from a generic platform in a linear supply chain. One product dominates 70% of the market while the remaining three take 10% of the demand each. The dominating product is randomly selected and changes every cycle. Although the total demand is constant, the demand for each product changes randomly. Our simulation results indicate that the hybrid information strategy is a powerful strategy (see Fig. 8). The results show that the hybrid information sharing strategy experiences 20% decrease in inventory and 3.45% increase in fill rate. The hybrid strategy offers better customer service than other information sharing models while reducing the inventory considerably. The results also show that applying just one of the basic models of Section II to the supply chain has problems. While the demand information sharing policy dramatically lower the supply chain inventory, the reduced inventory jeopardizes customer service under volatile demand mix. Although the inventory information sharing policy gives good customer service, the bullwhip effect may drive the inventory up.

V. DISCUSSION

Companies have long been aware of the value of information sharing in supply chains; however, there has not been much research on what kind of information supply chain members should share and how to share it in order to achieve the appropriate supply chain performance. Our study offers the following insights into these long-standing concerns. First, information sharing helps counter the phenomenon of demand variability amplification, mainly caused by the time lag between channel partners and the safety stocks in the supply chain. In traditional supply chains, orders are the only information channel members exchange. These orders are often misleading data highly distorted by the lead times and the high safety stocks at the downstream stages and convey very limited portion of real demand information. This information distortion is further magnified as it is further upstream in the supply chain and consequently the increased order variability leads to overstocking throughout the system. There may also be a high backlog and a low fill rate since a boom-and-bust order pattern results in a very high inventory at some times and a complete stockout at other times. The demand information sharing policy reduces the bullwhip effect to a large extent while the inventory information sharing policy and the shipment information sharing policy reduce at least one level of information distortion.

Second, the impact of information sharing on supply chain performance largely depends on the underlying demand process and the supply chain structure. There is no information sharing policy that is uniformly superior to the others because each supply chain has its unique characteristics. In this paper, we first consider a generic supply chain of a single product in order to study how the benefits of information sharing policies are influenced by demand patterns. We find out that various information sharing schemes unanimously improve supply chain performance under relatively stable demand. When the variance of consumer demand is high, however, different information sharing strategies affect different performance measures differently. The demand information sharing policy can significantly reduce the bullwhip effect and thus the safety stocks. But the minimum safety stock at each stage causes an increase in backlog and a drop in fill rate when the end-demand variability is high. Although the inventory information sharing policy does not perform as well as the demand information sharing policy in terms of inventory savings, this strategy is able to maintain a high fill rate by maintaining sufficient inventory. Like the inventory information sharing policy, the shipment information sharing policy can reduce one level of information distortion and thus supply chain inventory. By not considering backlog, it underestimates the downstream demand and may lead to a high backlog and a low fill rate when demand is highly unpredictable. Therefore, corporations often need to trade-off gains in some performance metrics against losses in other measures.

We then consider a more realistic supply chain that carries a customized product with multiple models in order to study how the benefits of information sharing policies are influenced by the product mix uncertainty and the supply chain structure. When a supply chain is faced with only demand volume variability, inventory buffers in its distribution network can be used to absorb the variability. Actually, retailers usually have to hold more inventory than necessary in order to show a full shelf so that the stores look like they are 'in business.' When a supply chain is faced with highly volatile demand mix, however, the use of finished goods inventory (FGI) is not only very costly but also inflexible. When there are rapid changes in customer preferences and/or introduction of new improved products, some of the products already made and held in inventory would have a reduced value or simply become obsolete. This is especially true for customizable products and innovative products. So we proposed a hybrid information sharing policy that utilizes the strengths of both the demand information sharing policy and the inventory information sharing policy for managing the supply chain with volatile product mix.

The hybrid strategy is an important insight for many good reasons. First of all, the demand information sharing policy in the distribution network can reduce the bullwhip effect and convey market signals quickly. This is becoming more important as there is a market trend to move closer to a sense-and-response model based on the anticipation of the consumer needs. Fast, accurate, real-time information sharing makes it possible to share inventories and capability status, and to respond to customer orders quickly. For example, Cisco Systems receives more than 90 percent of its orders on its Web site and outsources production of many of its units. Contract manufacturers monitor the orders and build equipment configured to customer demands while Cisco adds software and tests the equipment at the supplier's site. More than half the orders are delivered directly to the customer. Through sharing of demand information, Cisco allows customer-configured orders to be fulfilled quickly without adding capacity and reduces its time to market for new products. In this case, inventory and excess capacity are substituted by the value of information sharing. In addition, the demand information helps each stage make segment-specific forecasts and deploy FGI properly to buffer against product mix variability.

Secondly, product mix variability is minimized since each stage in the supplier network can benefit from the risk pooling effect and consequently make accurate forecasts to minimize inventories and improve customer service performance. As mentioned above, the inventory information sharing policy gives the best customer service in a high fill rate and a low backorder. This policy has the most advantages for the supplier network, where the availability and responsiveness of suppliers will be critical for the manufacturer's production planning and scheduling.

Finally, since many suppliers, particularly the second-tier or third-tier suppliers, usually are smaller companies with limited financial resources and technical expertise, it is infeasible and very expensive to use real demand information to drive decisions. Hence, the use of one-stage inventory information sharing to improve service level and responsiveness is appropriate for them. Therefore, the hybrid information sharing policy, which uses the demand information sharing policy in the distribution network to reduce demand variability associated with product mix while using the inventory information sharing policy in the supplier network to guarantee the reliable supply of components, is a powerful concept for managing product mix uncertainty. The radio manufacturer mentioned earlier is moving from multiple demand forecasts based on inaccurate, highly distorted order information to a single forecast based on real demand in its distribution network while still using the schedule sharing strategy in its supply network to maintain a high level of availability.

A great deal of controversy exists about the impact of information sharing on supply chain performance in the literature. While some authors have reported very beneficial impact, others have found marginal, no, or negative impact. The main reason for such great discrepancy is that different authors make different assumptions while actual supply chains are very complex, so it is impossible to meaningfully compare their results. Likewise, our results are general in the same spirit of many successful practices and hold implications for other general settings.

More studies are needed to look into matching the product, demand process, production and distribution process, and supply chain structure with the right information sharing strategies. This paper has only examined two information sharing schemes (one-stage inventory and demand sharing, and one-stage shipment information sharing) between the two extremes of no information sharing and real-time demand information sharing, and only one hybrid sharing approach. Other forms of sharing schemes and hybrid combinations could be developed and applied to various demand and supply situations.

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FIGURES

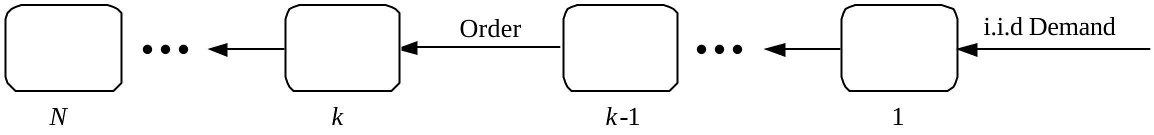

Fig. 1. Model 0 — The order information sharing policy.

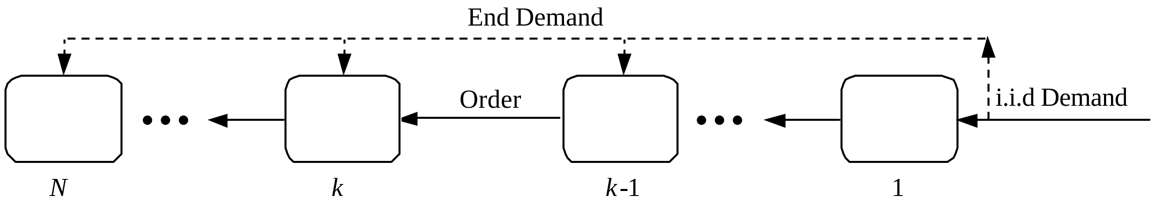

Fig. 2. Model 1 — The demand information sharing policy.

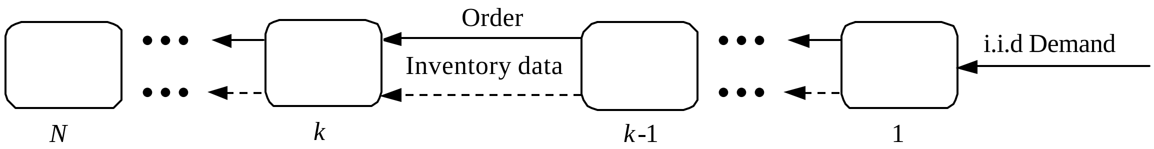

Fig. 3. Model 2 — The inventory information sharing policy.

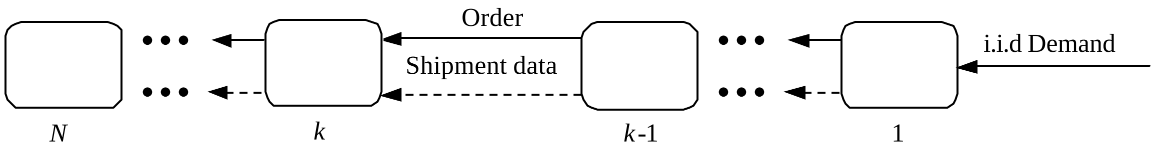

Fig. 4. Model 3 — The shipment information sharing policy.

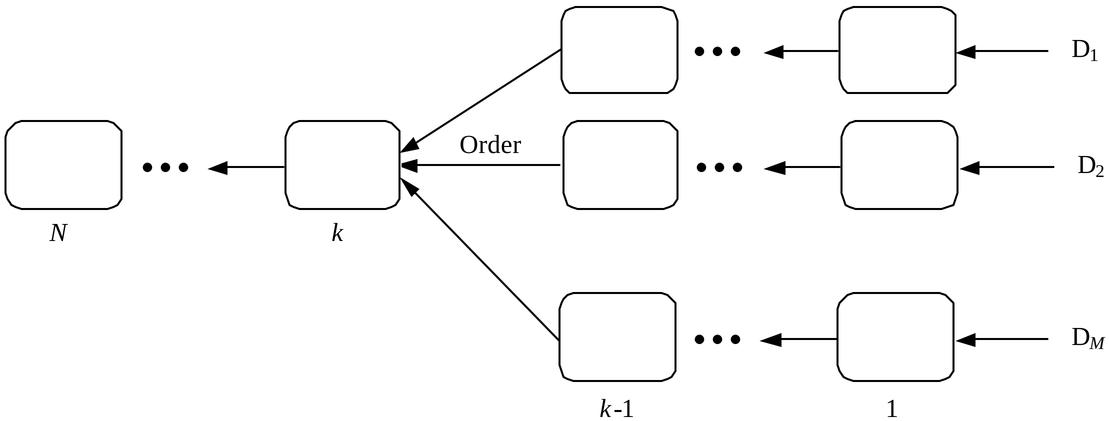

Fig. 5. Products assume their identity after stage k.

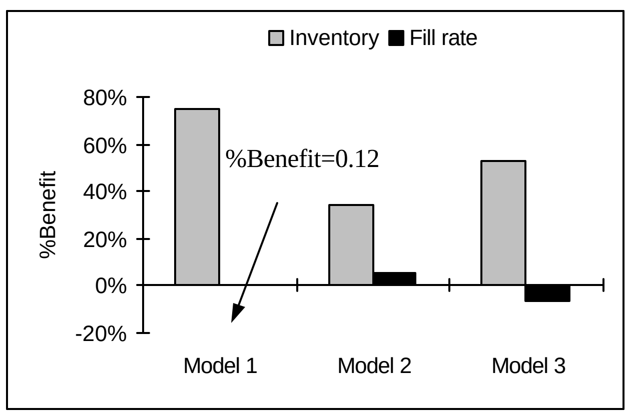

Fig. 6. Benefits comparing Models 1-3 with Model 0 for low demand variability.

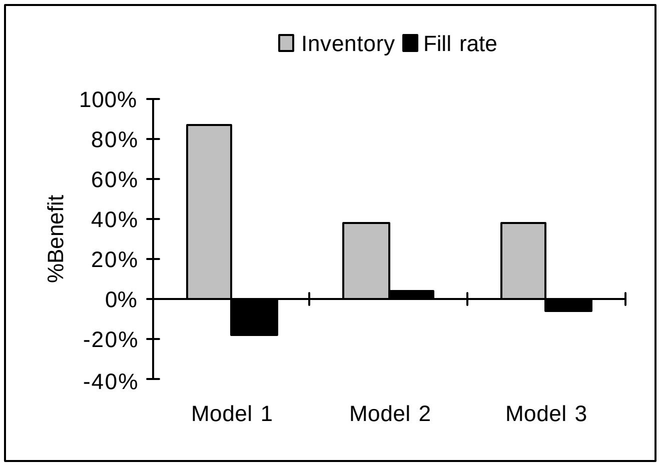

Fig. 7. Benefits comparing Models 1-3 with Model 0 for high demand variability.

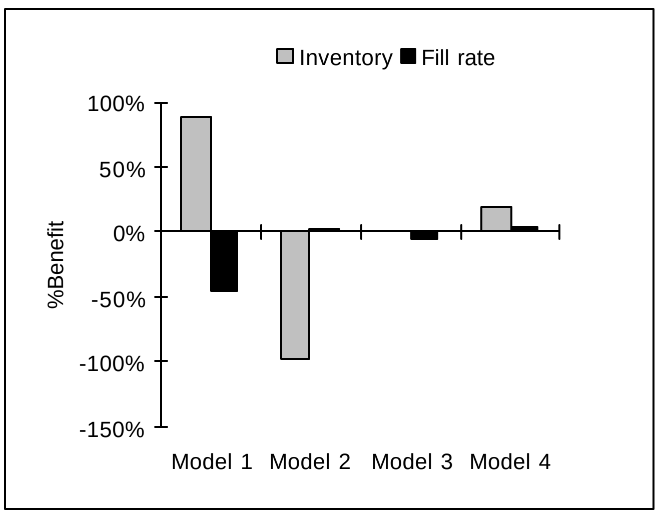

Fig. 8. Benefits comparing Models 1-4 with Model 0 for volatile product mix.