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The impact of forecasting model selection on the value of information sharing in a supply chain

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Abstract

This paper presents a study on the impact of forecasting model selection on the value of information sharing in a supply chain with one capacitated supplier and multiple retailers. Using a computer simulation model, this study examines demand forecasting and inventory replenishment decisions by the retailers, and production decisions by the supplier under different demand patterns and capacity tightness. Analyses of the simulation output indicate that the selection of the forecasting model significantly influences the performance of the supply chain and the value of information sharing. Furthermore, demand patterns faced by retailers and capacity tightness faced by the supplier also significantly influence the value of information sharing. The result also shows that substantial cost savings can be realized through information sharing and thus help to motivate trading partners to share information in the supply chain. The findings can also help supply chain managers select suitable forecasting models to improve supply chain performance.

Keywords: Supply chain management; Simulation; Forecasting; Information sharing

1. Introduction

Supply chain management (SCM) has attracted increasing attention in the academic community and in companies looking for practical ways to improve their competitive position in the global market. SCM relates to the co-ordination of products and information flows among suppliers, manufacturers, distributors, retailers and customers. In order for the different partners in a supply chain to co-ordinate their activities, they have to share information. Although modern information-technology tools are available, the costs for setting up and operating an information sharing system between 'links' of a supply-chain are still substantial. Furthermore, many companies are reluctant to

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share information with their trading partners, afraid that the information will be used unfairly to their disadvantage. In order to motivate these companies to share information, they need to be aware of the benefits that information-sharing systems can bring.

Many factors influence the performance of a supply chain. One important factor is the accuracy of the forecasts used by different parties in making their planning decisions. Because most retailers do not know their demand with certainty, they have to make their inventory decisions based on demand forecasts. With inaccurate forecasts, the quantity of materials ordered does not match the demand. These errors in the retailer's forecasts are passed to the supplier in the form of distorted orders. Lee et al. (1997) showed that the demand variability can be amplified upstream in the supply chain as the orders are passed from retailers to the distributors. Inaccurate forecasts can, therefore, significantly influence the performance of the supply chain in terms of increased inventory costs, backorders or loss of sales, and customer goodwill throughout the supply chain. They can also cause low utilization of capacity and other problems in production.

To improve the performance of a supply chain under demand uncertainty, it is suggested that companies in the supply chain share information and co-ordinate orders (Lee et al., 2000). Zhao et al. (2001) proposed and evaluated different methods of information sharing among retailers and suppliers, where retailers used simple moving-averages to make demand forecasts. It is not clear whether their conclusion would still hold under other forecasting assumptions. The purpose of this study is to examine how the selection of forecasting models influence the performance of the supply chain and the value of information sharing. This sort of knowledge will help companies in the supply chain select an appropriate forecasting model under information sharing and minimize the negative impact of demand uncertainty on supply chain performance.

In the following sections, we first review the related literature, and then describe the simulation model and the procedures of the simulation experiment. We next discuss the independent and dependent variables in the model and the hypotheses to be tested. Finally, we present our results and analyses and suggest directions for further studies.

2. Literature review

Many companies use modern information technology to help them gain competitive advantages in the marketplace. The rapid advancement in information technology has provided tools to enable trading partners in supply chains to share information with each other. Yet, what benefits can be gained through the sharing of information is a question that is frequently asked. Several researchers have examined the impact of information sharing on business performance.

Strader et al. (1999) described how the application of current information technology, such as the EDI and the Internet, have helped companies to share information and examined the impact of information-sharing on supply-chain order-fulfillment performance. Using computer simulation, they examined the performance of a divergent differentiation supply chain under various information-sharing strategies. They found that sharing both supply- and demand-information helped to substantially reduce inventory costs in a make-to-stock or assemble-to-order environment. Sharing supply information also substantially reduced order cycle time in an assemble-to-order environment.

Srinivasan et al. (1994) investigated the investigated the impact of vertical information integration using EDI on the shipment performance of suppliers in a just-in-time (JIT) environment. Through analyses of supplier shipment data in the automobile industry, they found that investment in the establishment of integrated information links to support information-sharing of JIT schedules significantly reduce the level of shipment discrepancies. However, the scope of the study is only on the manufacturer–supplier relationship and is based on shipment data of only one US manufacturer. In another study, Srinivasan et al. (1995) analyzed the data of a decade from the assembly centers of Chrysler Corporation.

They estimated the dollar benefits of improved information exchanges between Chrysler and its suppliers as a result of the use of EDI, amounted to $100 per vehicle and the total system-wide savings were about $220 million per year for the company.

Gavirneni and Tayur (1998) analyzed four inventory control models to study the benefits of information flow and delayed differentiation. They assumed that retailers used an order-up-to inventory policy and face demand with normal, uniform and Erlang distributions. Using a discrete-time framework, they found that the optimal policy is a state-dependent order-up-to policy for each model and showed how the optimal parameters can be computed. Comparison of the optimal policies of these four models revealed that information flow should be preferred over delayed differentiation when there are high holding costs or low penalty costs for shortage, high capacity, moderate variances or unequal numbers of customers. This choice is more beneficial when two or more of these conditions exist simultaneously. They also found that the two strategies (information flow and delayed differentiation) complement each other well when used simultaneously. However, the information flow studied only involves the sharing of inventory information from the retailer to the supplier and the supply chain considered consisted of only one supplier and up to two retailers.

Another related stream of research is the impact of the bullwhip effect on supply chain performance. Lee et al. (1997) analyzed the demand variability amplification along a supply chain from retailers to distributors, and named this amplification effect the *bullwhip effect*. They made a significant contribution by identifying four causes for the bullwhip effect and mathematically proved that the demand variation was amplified when orders were passed to the supplier. However they did not investigate the impact of the bullwhip effect on the costs in the supply chain, and did not discuss in detail strategies for reducing the impact of the bullwhip effect on the performance of the supply chain.

Chen et al. (2000) quantified the bullwhip effect for a simple, two-stage supply chain consisting of a single retailer and a single manufacturer. They assumed that demand followed an AR(1) process, and the retailer used a moving-average model for demand forecast and a simple order-up-to inventory policy for replenishment. Under these assumptions, they demonstrated that the variance of the orders was always higher than the variance in demand. Furthermore, the magnitude of the variance was significantly influenced by the number of observations used in the moving average, the lead-time between the retailer and the manufacturer, and the correlation parameter in the demand function. They extended the analytical model to a multiple-stage supply chain and found that the bullwhip effect could be reduced, but not completely eliminated, by sharing demand among all parties in the supply chain. In another paper, Chen et al. (2000) investigated the impact of forecast methods and demand patterns on the bullwhip effect. They compared an exponential-smoothing forecasting model and a moving-average model, and also compared a correlated demand with a demand with a linear trend. They found that reduction in ordering lead-time, and using more demand information in forecasting (the smoother forecast), could decrease the bullwhip effect. They also found that negatively correlated demand could lead to a larger increase in order variability than positively correlated demand, and that a retailer forecasting a demand with a linear trend will have more variable orders than a retailer forecasting an i.i.d. demand. These two papers evaluated the magnitude of the variance amplifications in the supply chain by considering alternative demand processes and forecasting models for a simple supply chain structure. However, they did not consider the impact of the variance amplifications on the cost and service level of the supply chain, nor did they consider inventory/ordering/setup costs or production decisions by the manufacturer.

Most of the current studies in the bullwhip effect focus on the distortions in demand information as one proceeds upstream in the supply chain. Although these studies provide insights into variations in quantity for materials or goods, the financial impact of inefficiencies of the bullwhip effect have seldom been explored.

Metters (1997) studied the impact of the bullwhip effect on profitability by establishing an empirical lower bound on the cost excess of the bullwhip effect. Results indicate that the importance of the bullwhip effect to a firm differs greatly depending on the specific business environments, and that eliminating the bullwhip effect can increase product profitability by 10–30% under some conditions. Although these results expressed the significance of the bullwhip effect in monetary terms, retailers were not involved in the study and the demand for the capacitated supplier was not based on the retailer's orders but was generated separately with different variations. Furthermore, these results did not consider ordering costs, transportation costs nor production setup costs.

Our review of the literature indicates that most studies in the supply chain area made many assumptions in an attempt to solve the problem analytically. While these studies helped practitioners understand the basic phenomenon, they did not provide sufficient guidelines for practicing managers to minimize the impact of demand uncertainty on the performance of the supply chain.

Using a simulation model, Johnson et al. (1999) examined the impact of vendor managed inventory (VMI) in less-than ideal environments – those with high demand volatility, partial adoption of VMI, and limited manufacturing capacity. VMI was modeled as a reduction in ordering frequency from the retailers to the supplier (from every four weeks to every two weeks, every week, or even daily). They found that the operational benefits associated with VMI were very compelling. They showed that the VMI approach greatly reduced inventories for all participants in the supply chain without compromising service. However, they did not measure the benefits in cost terms.

Zhao et al. (2001) evaluated different methods of information sharing through simulation. They assumed that the retailers used a simple moving-average model to make demand forecasts. It is not clear whether the conclusions still hold under the other forecasting models, and how the selection of the forecasting model by the retailer influences the performance of the supply chain and the benefits gained through information sharing.

While the impact of forecasting model selection on supply chain performance has not been investigated extensively, several researchers have investigated the impact of forecasting on the performance of materials requirement planning (MRP) systems. Zhao and Lee (1993) studied the impact of forecasting models and the selection of master production schedule (MPS) freezing parameters on the performance of MRP systems. Comparing the double exponential smoothing (DES) and Winters' method (WIN), they found that although Winters' method produced a lower bias and standard deviation of forecasting errors, it resulted in higher total costs and schedule instability. In another paper, Zhao et al. (1995) studied the impact of forecasting models on the performance of lot-sizing rules and the selection of MPS freezing parameters using the same two forecasting models. They found that using different forecasting models resulted in different bias and standard deviations of forecasting errors, and the forecasting errors often have a significant impact on the relative performance of the lot-sizing rules and MPS freezing parameters.

The review of the literature in the area of the impact of the forecasting model on the performance of material requirements planning systems indicates that the selection of forecasting model can significantly influence the performance of a production and inventory system. Understanding how a forecasting model influences system performance can help practitioners select better forecasting model to minimize the negative impact of forecasting errors. By the same token, understanding how forecasting model selection influences the performance of supply chain systems can also help supply chain managers improve supply chain performance. In this study, we build a comprehensive computer simulation model to capture the benefits of information sharing between the retailers and suppliers in a supply chain when the retailers utilize different forecasting models under different demand patterns. The analyses of the simulation output allow us to gain an understanding as to how forecasting model selection influences supply chain performance and the benefits of information sharing for both the suppliers and the retailers.

3. The simulation model and procedures

3.1. Basic assumptions

This study focuses on a piece of the supply chain consisting of one supplier and four retailers. The supplier is a manufacturer who produces a single product for four retailers. Production involves the consumption of one resource, of which the supplier has a (fixed) limited amount available. No explicit manufacturing lead-time will be considered, as this would depend on the supplier's capacity and will be implicitly determined in the supplier's production decision. Shipments are made from the supplier to retailers by truck and the transportation lead-time is assumed to be one period. We assume that the truck capacity is large enough (or equivalently, the product is small enough) so that all units ordered by a retailer in each period can be shipped by a single truck; thus, transportation costs are incurred for each order. The transportation costs per truck from the supplier to the retailers are taken from a real case ($450, $255, $331 and $553 for the four retailers, respectively) and are borne (mostly) by the retailer. In addition, there is also an order-processing cost ($30 per order) incurred whenever a retailer places an order to the supplier. Thus, in the retailer's economic ordering quantity (EOQ) model for making ordering decisions, the value of the "ordering cost" parameter is taken to be the sum of the order-processing cost and the transportation costs. The production setup cost of the supplier is assumed to be $500 per setup. The unit inventory costs per period for the supplier and the retailers are $0.03 and $0.04, respectively, which correspond to an inventory-carrying percentage of 0.1% per period. The unit backorder cost per period for the supplier and the retailers are $0.03 and $0.04, respectively, which correspond to an inventory-carrying percentage of 0.1% per period. The unit backorder cost per period for the supplier and the retailers are $0.30 and $0.40 (equivalent to 1% of the unit cost), respectively. Similar cost parameters have been used in previous studies on MRP (e.g., Ebert and Lee, 1995).

The retailers face uncertain customer demands, with the average demand per period for each retailer being 1000 units. The retailers replenish their inventories by placing orders to the supplier, thus average demand per period for the supplier is 4000 units. The lead-time for the retailers to place an order to the supplier is assumed to be zero. Sufficient initial inventory is assumed for each retailer; this also minimizes the effect due to initial conditions. In this study, we set the initial inventory for the ith retailer at $(4+i)\times 1000$ $(i = 1,2,3,4)$. Since the transportation lead-time used in this simulation is one period, an initial inventory of 4×1000 units is sufficient to cover the demand for the initial periods. The other part of the initial inventory ($i\times 1000$ units) is used to give different retailers different initial inventories.

The simulation procedure comprises three phases, which are described below.

3.2. Phase I: Generation of demand and capacity

The first phase of the simulation generates demand for all the retailers and calculates the available aggregate capacity for the single resource of the supplier.

All four retailers are assumed to face identical demand patterns generated by the following formula:

$$\begin{aligned} Demand_t = {} & base + slope \times t \\ & + season \times \sin\left(\frac{2\pi}{SeasonCycle}\times t\right) \\ & + noise \times snormal(), \end{aligned} \tag{1}$$

where $Demand_t$ is the demand in period t, $snormal()$ is a standard normal random number generator and $SeasonCycle = 7$ in this study. The other parameters (*base*, *slope*, *season*, and *noise*) are characteristic parameters for demand patterns, among which *base* is selected to ensure that the average demand for all the simulation periods is 1000.

Four demand patterns (CON, SEA, SIT, SDT) representing different combinations of trends and seasonality are used in this study. The characteristic parameters of these demand patterns are shown in Table 1. CON produces demand with neither trends nor seanonality, SEA produces

Table 1
Characteristics of demand patterns

Demand pattern	*base*	*slope*	*season*	*noise*
CON	1000.0	0	0	100
SEA	1000.0	0	200	100
SIT	551.0	2	200	100
SDT	1449.0	−2	200	100

demand with seasonality but without trends, SIT produces demand with seasonality and an increasing trend, and SDT produces demand with seasonality and a decreasing trend. When different forecasting models are used to forecast demand produced by different demand generators, different levels of forecasting errors will appear.

In this study, we assume that the capacity absorption for each unit of product is 1, that is, one unit of resource is required by the supplier to produce exactly one unit of product. This assumption has no loss of generality, because the demand can always be scaled by the units of the resource needed for production. Once the demand for all retailers is generated for the simulation periods, the total capacity needed to produce all the items for all the periods can be calculated (equal to the total demand of all retailers over all the periods). In order to generate the available capacity for each period, we introduce a parameter – capacity tightness (CT) – to indicate the ratio of the total available capacity to the total capacity needed. The total capacity available for all the periods is equal to the total demand multiplied by CT factor. We assume that this total capacity available is evenly distributed among all the simulation periods.

3.3. Phase II: Retailers' ordering decisions

The retailers are assumed to use the EOQ rule to determine their ordering quantity. In each period, the retailers use a forecasting method to forecast demand for the future periods. Five typical forecasting models:

- a naïve method (NAV),
- a simple moving average (SMA),
- a two-parameter double exponential smoothing (DES),
- a no-trend Winters' method (NTW), and
- a three-parameter Winters' model (WIN)

are studied in this paper. Based on their demand forecasts, the retailers decide when and how many units to order from the supplier using an EOQ policy, but only the current period's order is placed to the supplier.

The forecasting models SMA, DES, NTW and WIN need one or more parameters whose values are estimated based on minimizing the mean absolute deviation (MAD) of the forecasting errors. The forecasting parameter(s) will be re-estimated once the schedule is rolled one period ahead and more demand information becomes available.

After placing its order, the retailer receives the delivery shipped by the supplier one period ago (since the transportation lead-time is one period). Then, at the end of the period, the actual customer demand is realized. The retailer fills the customers' demand (plus backorders if there are any) with on-hand inventory, and any remaining shortages will become backorders.

3.4. Phase III: Supplier's production and delivery decisions

The supplier/manufacturer applies a single-item-capacitated lot-sizing rule (Chung and Lin, 1988) in planning his/her production activities. The supplier receiver orders from different retailers and makes production-planning decisions based on information available. We consider three cases:

1. When there is no information sharing between the supplier and the retailers, the supplier makes production decision based only on the orders placed by the retailers (i.e. make-to-order).
2. When the retailers share their forecasted net requirements with the supplier, both the orders placed and the net requirements forecasted by the retailers are used as gross requirements by the supplier in its production decision.
3. When the retailers share their planned orders with the supplier, both the placed orders and

the planned orders shared by the retailers are used as gross requirements by the supplier in its production decision.

Only the current period's production plan is implemented.

At the end of each period, after production for the current period is finished, the supplier makes shipping decisions from on-hand inventory. The supplier fills each retailer's order (plus any backorders) if on-hand inventory is sufficient to fill all the retailers' orders and backorders. If on-hand iventory is not sufficient, each retailer will be allocated a quota proportional to its order (plus any backorders) and any shortages will become backorders. A shipment will arrive at the retailers via truck according to the transportation lead-time. As we mentioned previously, we assume the truckload is large enough so that a single truck can complete a shipment to any retailer in any period.

The party to whom the transportation costs will be charged depends on whether that particular shipment is initiated due to an order placed by the retailer. When the retailer places an order in the current period, it also picks up the bill for the transportation costs for the current period's shipment, regardless of whether a proportion of the shipment is used to satisfy backorders. When a retailer does not place an order in a current period and the shipment to the retailer is used only to satisfy the backorders, then the supplier picks up the bill for the transportation costs for the current period's shipment.

This process is repeated until ordering, production and delivery decisions are developed for all the simulation periods. After the entire simulation run is completed, the inventory costs, order-processing and setup costs, backorder costs, transportation costs, total costs and customer service level will be calculated for the retailers and the supplier. The aggregate total cost and service level will also be calculated and used as the performance measure of the supply chain.

3.5. Verification and validation

The simulation program is written in C++, a popular object-oriented programming language, and run on a Sun-Sparc workstation under the Unix operating system. Throughout the development of the program, the model is validated and the codes are verified using a large number of testing techniques and testing data sets. Whenever a module, procedure, subroutine or function is created, it is individually verified to be correct using some benchmark testing cases. After the verification for the individual modules one-by-one, the correctness of the whole simulation program is tested. We have run and traced the simulation program step-by-step for several sets of initial input data, and checked the results at each step with the results calculated by hand, to ensure that the program logic and processing are error-free. We also tested some typical benchmark inputs and verified that the outputs generated by the program are as expected from the model.

The length of the simulation run is selected in such a way that the termination effect will be minimized. The first 50 periods are used to estimate the initial parameters for the forecasting models and the last 10 periods are excluded from the calculation of the performance measures to eliminate the effects of transportation and ordering lead-times. Therefore, the final performance measures are calculated based on 350 simulation periods (from period 50 to period 399). These cut-off values were determined empirically; detailed examination of the model indicated that steady state has been reached. In fact, we have also run the simulation with 40, 50, and 60 being the starting period and 360, 410, and 460 being the ending period, respectively. The results from simulation runs under all nine combinations of the starting and ending periods are in general agreement with the primary findings from this study. Thus, in the detailed discussion of our findings in Section 5, we refer to results obtained using the cut-off values of 50 and 400 in our simulations.

We also performed sensitivity analysis for the cost structures of the supply chain by systematically changing the values of the holding costs and backorder costs for the supplier and retailers over practical ranges of interest, with anticipated effects on model behavior, further confirming the model's validity. Since the variations in the cost structure does not impact our major findings (which will be detailed in Section 5), therefore we exclude the cost structure from the independent factors in order to focus on the major concerns of this study.

Finally, to reduce the impact of random variations, five replicates were conducted for each combination of the independent variables, which will be introduced in the following section.

4. Experimental design and research hypotheses

4.1. Independent variables

There are two major groups of independent variables in this simulation experiment. The first group of independent variables is the environmental factors or operating conditions of the systems, which includes the demand pattern (DP) faced by the retailers, and the capacity tightness (CT) faced by the supplier. The second group of independent variables is the parameters for SCM, which includes the forecasting model (FM) used by the retailers, and the way that information is shared between the supplier and the retailer (IS). The number of levels of these parameters and their values are discussed in detail below:

- Retailer's demand pattern (DP): Four demand patterns (CON, SEA, SIT, SDT) representing the different trends and seasonalities are used in this study as discussed in the previous section.
- Supplier's capacity tightness (CT) refers to how tight the supplier's production capacity is relative to the demand. It is equal to the total capacity available divided by the total demand to be satisfied. Three levels of capacity tightness, i.e. Low (1.33), Medium (1.18) and High (1.05) are used in this study. They correspond to resource utilization of 75%, 85% and 95%, respectively.
- Retailer's forecasting model (FM): Five typical forecasting models, NAV, SMA, DES, NTW, WIN are studied in this paper. To provide a benchmark of comparison, we have also included the case where there is no demand uncertainty (FM = ACT), that is, when the actual demand in future periods are known and thus the forecast is perfect.
- Information sharing (IS) refers to the way that information is shared between the supplier and the retailers. Three cases will be examined. In the case of no information sharing (NIS), retailers do not share any information with the supplier; the supplier receives only orders from the retailers and makes production-planning decisions according to these orders. In the case of demand information sharing (DIS), retailers share their forecasted net demand with the supplier. At each period, the retailers not only make their own demand forecasts and inventory replenishment decisions and (possibly) place an order to the supplier at a time, they also inform the supplier of their net requirements in the future. Thus, although the supplier does not know the inventory policy of the retailers, he/she will know the forecasted net requirement for each retailer, and can use both the order and forecasted demand information from the retailers to make its production-planning decisions. In the third case of order information sharing (OIS), all retailers will make demand forecasts for the future periods, develop future order plans and share their order plans with the supplier. In this case, the supplier can plan production activities based on the future order plans of the retailers as well.

4.2. Dependent variables

The following performance criteria will be used as the dependent variables of the experimental design:

- Total cost for retailers (TCR), which is the sum of ordering costs (including transportation costs), inventory carrying costs and the backorder costs for the retailers.
- Total cost for the supplier (TCS), which is the sum of the setup costs, transportation costs (for backorder delivery), inventory carrying costs and the backorder costs for the supplier.
- Total costs for the entire supply chain (TC), which is the sum of the TCR and TCS, minus backorder costs paid by the supplier to the retailers. We subtract backorder costs because

they are only an internal cost within the supply chain.

- The service level of the supplier (SLS), which is the percentage of retailers' orders satisfied through the on-hand inventory of the supplier. This is an internal service performance measure within the supply chain.
- The customer service level of the retailers (SLR), which is the percentage of customer demand satisfied through the available inventory of the retailers. We average this for all 350 simulation-periods and the four retailers. SLR is also the actual external service performance of the entire supply chain.

4.3. Research hypotheses

The output from the simulation experiments will be analyzed to test the following three research hypotheses:

Hypothesis 1. FM selection by the retailer will significantly influence the performance of the supply chain and the value of information sharing. The forecasting model with higher forecast accuracy will reduce costs, improve service level, and make information sharing more beneficial by improving the performance of the supply chain.

Hypothesis 2. DP faced by the retailers significantly influences the impact of forecasting model on the value of the information sharing. The presence of trends and seasonality in the DP will make the impact of forecasting model selection on the value of information sharing more significant.

Hypothesis 3. CT faced by the supplier will also significantly influence the impact that the forecasting model will have on the value of the information sharing. When the supplier faces a higher CT, the more significant will be the impact that the selection of forecasting model by the retailer will have on the value of the information sharing.

Our simulation results can also be used to compare the value of information-sharing under different demand patterns.

5. Results

The output from the simulation experiments was examined by analysis of variance (ANOVA) and Duncan's test, using SAS. Selected ANOVA results are presented in Table 2.

5.1. The impact of FM on supply chain performance and the value of IS

Table 2 shows that the most significant main effects influencing the total costs of the supply chain are the CT faced by the supplier, the DP faced by the retailers, and the IS method between the supplier and the retailers. The selection of forecasting model is also significant in influencing total costs and service levels for both the supplier and the retailers, and the total costs for the entire supply chain. Furthermore, the interaction between FM and IS has a significant impact on all five dependent variables at the 5% significance level.

To examine the impact of the forecasting model on the performance of supply chain and the benefits of information sharing, the performance of FM and IS is presented in Table 3. RTC, RTCS and RTCR represent relative TC, TCS and TCR, respectively, and are calculated by dividing the specified TC, TCS and TCR by the minimum TC, TCS and TCR among the different values of the corresponding independent variables.

Examination of Table 3 reveals that: Under all forecasting models, OIS performs better than DIS and DIS performs better than NIS according to all five criteria. Furthermore, the supplier enjoys a greater cost reduction than the retailers as a result of sharing information regardless of the forecasting models used. Because the differences between retailers' service levels (also the service levels of the entire supply chain) under different conditions are relatively small, in the following sections we will focus our discussion on the performance of information sharing under different forecasting models according to total costs.

The performance improvements of OIS over DIS, and DIS over NIS under different forecasting models are quite different. OIS over NIS shows the greatest total cost improvement (up to 41%) when

Table 2
Selected ANOVA results

Source	Dependent variables									
	TC[a]		TCS[b]		TCR[c]		SLS[d]		SLR[e]	
	F value	Pr > *F*	*F* value	Pr > *F*	*F* value	Pr > *F*	*F* value	Pr > *F*	*F* value	Pr > *F*
DP	63813.26	0.0001	51044.23	0.0001	70656.72	0.0001	780.25	0.0001	42204.65	0.0001
CT	99999.99	0.0001	99999.99	0.0001	61105.64	0.0001	5201.64	0.0001	40583.21	0.0001
DP * CT	30780.20	0.0001	21691.14	0.0001	27782.00	0.0001	90.21	0.0001	12187.99	0.0001
FM	422.82	0.0001	689.94	0.0001	259.77	0.0001	578.65	0.0001	200.27	0.0001
DP * FM	22.65	0.0001	36.44	0.0001	38.71	0.0001	41.69	0.0001	28.41	0.0001
CT * FM	15.94	0.0001	1.31	0.2177	31.23	0.0001	4.29	0.0001	19.64	0.0001
DP * CT * FM	6.69	0.0001	3.04	0.0001	12.30	0.0001	0.76	0.8171	4.35	0.0001
IS	9418.36	0.0001	19830.62	0.0001	81.31	0.0001	12504.48	0.0001	761.41	0.0001
DP * IS	76.01	0.0001	142.86	0.0001	933.11	0.0001	209.52	0.0001	143.24	0.0001
CT * IS	475.19	0.0001	194.40	0.0001	766.97	0.0001	23.68	0.0001	130.52	0.0001
DP * CT * IS	94.48	0.0001	143.63	0.0001	378.02	0.0001	89.37	0.0001	32.83	0.0001
FM * IS	143.31	0.0001	153.83	0.0001	2.96	0.0011	62.24	0.0001	17.51	0.0001
DP * FM * IS	5.05	0.0001	6.07	0.0001	7.69	0.0001	1.72	0.0100	3.92	0.0001
CT * FM * IS	6.24	0.0001	2.25	0.0014	7.37	0.0001	0.35	0.9968	2.83	0.0001
DP * CT * FM * IS	3.05	0.0001	2.59	0.0001	5.69	0.0001	0.75	0.9204	1.68	0.0012

[a] Based on residual analysis and suggestion by SAS, log transformation of TC (i.e. $\log_{10}(TC)$) was made to satisfy the assumptions of ANOVA.
[b] Based on residual analysis and suggestion by SAS, square-root transformation of TCS (i.e. sqrt(TCS)) was made to satisfy the assumptions of ANOVA.
[c] Based on residual analysis and suggestion by SAS, inverse square-root transformation of TCR (i.e. 1/sqrt(TCR)) was made to satisfy the assumptions of ANOVA.
[d] Based on residual analysis and suggestion by SAS, inverse transformation of SLS (i.e. 1/SLS) was made to satisfy the assumptions of ANOVA.
[e] Based on residual analysis and suggestion by SAS, square transformation of SLR (i.e. SLR^2) was made to satisfy the assumptions of ANOVA.

Table 3
Performance of information sharing under different forecasting models

Independent variables		Dependent variables									
FM	IS	TC		TCS		TCR		SLS		SLR	
		RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	141	2–3	185	2–3	128	3	67.09	2–3	97.43	2–3
	DIS	134	2–3	177	2–3	118	2	67.16	2–3	97.49	2–3
	OIS	100	1	100	1	100	1	92.95	1	98.25	1
NAV	NIS	144	2–3	202	2–3	130	3	63.38	2–3	97.32	2–3
	DIS	141	2–3	198	2–3	124	2	63.42	2–3	97.35	2–3
	OIS	124	1	153	1	113	1	74.82	1	97.64	1
SMA	NIS	143	3	191	2–3	130	3	67.22	2–3	97.54	2–3
	DIS	133	2	180	2–3	116	2	67.31	2–3	97.61	2–3
	OIS	107	1	116	1	101	1	86.70	1	97.98	1
DES	NIS	142	2–3	189	2–3	129	3	67.25	2–3	97.50	2–3
	DIS	137	2–3	184	2–3	123	2	67.29	2–3	97.53	2–3
	OIS	107	1	119	1	105	1	86.69	1	97.91	1
NTW	NIS	142	3	189	2–3	130	3	67.67	2–3	97.77	2–3
	DIS	132	2	177	2–3	116	2	67.77	2–3	97.84	2–3
	OIS	106	1	113	1	101	1	88.00	1	98.22	1
WIN	NIS	142	3	188	2–3	129	3	67.96	2–3	97.76	2–3
	DIS	134	2	179	2–3	118	2	68.04	2–3	97.81	2–3
	OIS	105	1	114	1	103	1	88.47	1	98.20	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different independent variables is set at 100. The relative total costs of the other independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

there is no demand uncertainty (FM = ACT), while costs improve only 16% (i.e. (144 – 124)/124) when FM = NAV. Differences in the value of information sharing under different forecasting models are caused by the differing forecast accuracy of the models. The higher the forecast accuracy, the greater the value of information sharing. When FM = ACT, we assume that demand is known with certainty and, thus, the information shared is 100% reliable. Under such a condition, information shared by a retailer with a supplier can produce the greatest benefits to the entire supply chain. Since Winters' model can recognize both seasonality and trends in demand, the forecast is unbiased and the standard deviation in forecast error is very small under FM = WIN. Therefore, its forecast accuracy and the benefits achieved through information sharing are higher than those attained from using other models. Since DES and NTW can recognize either seasonality or trends in demand, the forecast accuracy is also very high, and the benefits achieved through information-sharing are nearly the same as those under Winter's model.

Besides, when NAV, SMA, and NTW methods are used to forecast demand with trends, biases will exist in the forecast. However, SMA and NTW produce only a slightly larger standard deviation in forecast error than Winter's model, while the NAV method produces the largest standard deviation in forecast error among all forecasting model in this study. Therefore, the value of information-sharing is lowest when NAV is used as the forecasting model. Overall, the results in Table 3 indicate that higher benefits will be achieved through information sharing when the forecasting accuracy is higher, thus supporting Hypothesis 1.

Comparison of forecasting model performance under different levels of information sharing indicates that more accurate forecasts may not help to improve the performance of the supply chain dramatically when the retailers do not share information with the supplier. Actually, even using the Naïve model produces only a little higher total cost for the supply chain when no information is shared between the supplier and the retailers. When retailers share planned order information with the supplier, however, Table 3 clearly shows that knowing the actual demand (ACT) will incur the lowest total costs. Winters' model gives the next best result. The Naïve model produces much higher total costs.

Overall, the results in Table 3 support Hypothesis 1. Higher forecasting accuracy improves the performance of the supply chain and enhances the benefits of information sharing. Furthermore, the results also show that improvement in forecasting accuracy significantly improves performance in the supply chain only when information is shared.

5.2. The interaction between DP, FM and IS

ANOVA results in Table 2 show that at the 5% significance level, the three-way interaction DP $*$ FM $*$ IS has significant effects on all five dependent variables. The performances of IS and FM under different forecasting models are presented in Tables 4, 5, 6, and 7 for DP = CON, SEA, SIT, and SDT, respectively.

Examination of the results in Tables 4–7 clearly shows that both the demand pattern and the forecasting model have a significant impact on the value of information sharing in terms of all five-performance measures (TC, TCS, TCR, SLS, and SLR). However, the DP seems to have a much greater impact on system performance and the value of IS than the forecasting model. The impact of the DP and the forecasting models on supply chain performance and the value of IS are discussed below.

When DP = CON or SEA (shown in Tables 4 and 5, respectively), DIS performs as well as NIS under all cases. As to OIS, it outperforms DIS (and NIS) according to TC and TCS. However, OIS produces slightly higher total costs for retailers than DIS or NIS. When DP = CON or SEA, all retailers face demands without trends, thus the total demand of the supply chain is smooth over the time horizon and is usually below supplier's capacity in every period. Therefore, when retailers share their planned orders with the supplier, the supplier can make a better trade-off between setup costs and inventory costs through the capacitated

Table 4
Performance of information sharing under different forecasting models when DP = CON

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	146	2–3	359	2–3	100	1–2	67.74	2–3	99.61	2–3
	DIS	146	2–3	359	2–3	100	1–2	67.74	2–3	99.61	2–3
	OIS	100	1	100	1	117	3	99.66	1	100.00	1
NAV	NIS	155	2–3	376	2–3	113	1–2	68.05	2–3	99.65	1–3
	DIS	155	2–3	376	2–3	113	1–2	68.06	2–3	99.65	1–3
	OIS	126	1	179	1	128	3	88.02	1	99.73	1–3
SMA	NIS	153	2–3	368	2–3	112	1–2	68.54	2–3	99.76	1–2
	DIS	153	2–3	368	2–3	112	1–2	68.54	2–3	99.76	1–3
	OIS	119	1	143	1	129	3	94.23	1	99.85	1–3
DES	NIS	152	2–3	358	2–3	113	1–2	69.26	2–3	99.75	1–3
	DIS	152	2–3	358	2–3	113	1–2	69.26	2–3	99.75	1–3
	OIS	118	1	142	1	129	3	93.93	1	99.82	1–3
NTW	NIS	153	2–3	360	2–3	113	1–2	68.87	2–3	99.76	1–3
	DIS	153	2–3	360	2–3	113	1–2	68.87	2–3	99.76	1–3
	OIS	119	1	143	1	129	3	93.84	1	99.81	1–3
WIN	NIS	153	2–3	360	2–3	112	1–2	68.86	2–3	99.76	1–3
	DIS	153	2–3	360	2–3	112	1–2	68.86	2–3	99.76	1–3
	OIS	119	1	143	1	129	3	93.82	1	99.82	1–3

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

Table 5
Performance of information sharing under different forecasting models when DP = SEA

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	146	2–3	356	2–3	100	1–2	67.50	2–3	99.60	2–3
	DIS	146	2–3	356	2–3	100	1–2	67.50	2–3	99.60	2–3
	OIS	100	1	100	1	117	3	99.40	1	100.00	1
NAV	NIS	159	2–3	434	2–3	109	1–2	61.66	2–3	99.14	2–3
	DIS	158	2–3	434	2–3	109	1–2	61.70	2–3	99.14	2–3
	OIS	146	1	303	1	120	3	73.37	1	99.28	1
SMA	NIS	153	2–3	372	2–3	112	1–2	67.47	2–3	99.48	1–3
	DIS	153	2–3	372	2–3	112	1–2	67.47	2–3	99.48	1–3
	OIS	123	1	161	1	128	3	90.95	1	99.56	1–3
DES	NIS	153	2–3	370	2–3	112	1–2	67.28	2–3	99.36	2–3
	DIS	153	2–3	370	2–3	112	1–2	67.28	2–3	99.36	2–3
	OIS	121	1	155	1	128	3	91.51	1	99.45	1
NTW	NIS	151	2–3	353	2–3	113	1–2	68.98	2–3	99.77	1–3
	DIS	151	2–3	353	2–3	113	1–2	68.98	2–3	99.77	1–3
	OIS	118	1	141	1	129	3	93.81	1	99.85	1–3
WIN	NIS	151	2–3	353	2–3	113	1–2	68.98	2–3	99.77	1–3
	DIS	151	2–3	353	2–3	113	1–2	68.98	2–3	99.77	1–3
	OIS	118	1	141	1	129	3	93.81	1	99.85	1–3

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

Table 6
Performance of information sharing under different forecasting models when DP = SIT

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	138	2–3	176	2–3	127	2–3	66.42	2–3	95.30	2–3
	DIS	137	2–3	175	2–3	126	2–3	66.43	2–3	95.36	2–3
	OIS	100	1	100	1	100	1	89.47	1	96.99	1
NAV	NIS	137	2–3	190	2–3	124	2–3	61.92	2–3	95.40	2–3
	DIS	137	2–3	190	2–3	124	2–3	61.94	2–3	95.41	2–3
	OIS	125	1	156	1	114	1	70.05	1	96.04	1
SMA	NIS	136	2–3	178	2–3	125	2–3	66.47	2–3	95.71	2–3
	DIS	136	2–3	178	2–3	125	2–3	66.47	2–3	95.71	2–3
	OIS	112	1	124	1	107	1	82.15	1	96.49	1
DES	NIS	134	2–3	178	2–3	122	2–3	66.02	2–3	95.75	2–3
	DIS	134	2–3	178	2–3	122	2–3	66.02	2–3	95.76	2–3
	OIS	110	1	120	1	104	1	82.73	1	96.61	1
NTW	NIS	134	2–3	177	2–3	122	2–3	65.71	2–3	96.10	2–3
	DIS	134	2–3	177	2–3	122	2–3	65.71	2–3	96.10	2–3
	OIS	109	1	118	1	104	1	83.18	1	96.94	1
WIN	NIS	133	2–3	174	2–3	121	2–3	67.43	2–3	96.16	2–3
	DIS	133	2–3	174	2–3	121	2–3	67.43	2–3	96.16	2–3
	OIS	106	1	113	1	102	1	85.42	1	97.04	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.
[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.
[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

Table 7
Performance of information sharing under different forecasting models when DP = SDT

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	143	3	148	3	149	3	66.69	2–3	95.23	3
	DIS	129	2	135	2	131	2	66.95	2–3	95.41	2
	OIS	101	1	100	1	105	1	83.25	1	95.99	1
NAV	NIS	144	3	159	2–3	149	3	61.87	2–3	95.10	3
	DIS	137	2	152	2–3	140	2	61.99	2–3	95.20	2
	OIS	119	1	130	1	120	1	67.84	1	95.51	1
SMA	NIS	144	3	154	3	149	3	66.40	2–3	95.22	3
	DIS	123	2	135	2	124	2	66.77	2–3	95.47	2
	OIS	100	1	104	1	100	1	79.46	1	96.05	1
DES	NIS	143	3	153	3	149	3	66.44	2–3	95.16	3
	DIS	134	2	144	2	137	2	66.58	2–3	95.27	2
	OIS	107	1	111	1	108	1	78.57	1	95.77	1
NTW	NIS	144	3	154	3	149	3	67.13	2–3	95.44	3
	DIS	123	2	135	2	124	2	67.53	2–3	95.75	2
	OIS	101	1	105	1	102	1	81.17	1	96.29	1
WIN	NIS	144	3	154	3	150	3	66.57	2–3	95.34	3
	DIS	128	2	139	2	130	2	66.88	2–3	95.53	2
	OIS	105	1	108	1	106	1	80.82	1	96.11	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

lot-sizing procedure. Furthermore, when the information is shared, the supplier has a longer planning horizon and thus can make better use of its capacity, and dramatically reduce its backorder costs. The much higher service level of the supplier under OIS reflects this fact. As a result of the improvements in service levels to the retailers, the supplier saves a significant amount of money in terms of backorder penalty costs and possible transportation costs incurred to deliver the backorders to the retailers. This is why when DP = CON or SEA, the TCS improvement of OIS over NIS is often greater than 100%. The retailer's service level, however, is already very high even without information sharing, thus sharing information did not significantly reduce the backorder costs for the retailers when they share information with the supplier. On the other hand, the retailers' inventory carrying costs increase dramatically as a result of the increase in supplier service level. This explains why total costs for the retailers are even higher with OIS.

When all the retailers face demands with trends (Tables 6 and 7 for DP = SIT and SDT, respectively), OIS performs better than DIS and DIS performs better than NIS for all five criteria regardless of the forecasting model used. When retailers have identical increasing demand trends (Table 6), NIS and DIS do not result in a significantly different performance for all five-performance measures. Therefore sharing demand information provides little benefit to the parties in the supply chain. However, the total cost savings as a result of sharing ordering information (OIS) are about 30–40% and the benefit lessens with a lower forecast accuracy. From Table 6 we can also see that sharing order information results in greater benefits for the supplier than for the retailers under all forecasting models.

When retailers face identical decreasing trends, the value of sharing demand and order information relative to no information sharing are slightly higher than the corresponding values when retailers face identically increasing trends. Furthermore, the values of information sharing are about the same for both the supplier and retailers. When DP = SDT, the total cost reductions as a result of sharing ordering information (OIS) range from 21% (i.e. $(144 - 119)/119$ for NAV) to 44% (i.e. $(144 - 100)/100$ for SMA) depending on the forecasting models used. When DP = SIT, however, the corresponding ranges are between 10% (i.e. $(137 - 125)/125$ for NAV) and 38% (i.e. $(138 - 100)/100$ for ACT).

The results in Tables 6 and 7 clearly show that higher benefits can be achieved by sharing information when retailers face decreasing trends. This is because that supplier can better utilize its capacity to meet demand when retailers share information under a decreasing trend. Under an increasing trend, the supplier does not have sufficient capacity to meet the demand towards the end of the simulation run even though the retailers share their information.

The demand pattern also significantly influences the relative performance of the forecasting models. When DP = CON or SEA, in terms of TC, TCS, and TCR, ACT always performs best and NAV performs worst, while WIN, NTW, DES and SMA performs nearly equally well between the two extremes. The level of information sharing does not influence the performance ranking of the forecasting models. The weakest forecast (FM = NAV) often resulted in an increase in total costs in the range of 20–50% relative to a perfect forecast (FM = ACT). The forecasting model used also significantly influences the value of sharing information. In general, higher cost savings can be achieved through information sharing when forecasting accuracy is higher. Furthermore, when a perfect forecast is used, the reduction in total costs by sharing planned order information (OIS) relative to NIS can be up to about 46%.

When DP = SIT and retailers share planned order information (IS = OIS), ACT and WIN produce dramatically lower TC than SMA and NAV. The SMA and NAV performed worst because they make forecasts with negative biases (under-forecasting) when DP = SIT. The negative bias in the forecast leads to a lower service level for both the supplier and the retailers. The lower service level, in turn leads to higher backorder costs and, thus, a worse performance.

When DP = SIT and retailers do not share any information (NIS) of share demand information (DIS) only, the performance differences, in terms of total costs between forecasting models, are relatively small. Surprisingly, forecasting models with higher forecasting accuracy do not result in lower costs when the retailers do not share information with the supplier. Actually, perfect demand knowledge (FM = ACT) actually produces the worst performance. This result contradicts the traditional wisdom that more accurate forecasts should lead to a better system performance. Similar observations were made in Materials Requirements Planning systems (see Zhao and Lee, 1993; Lee and Goodale, 1995).

The results clearly show that retailers have to improve forecasting accuracy and share information on planned orders so as to improve the performance of the supply chain. Improving forecasting accuracy without sharing information may not improve supply chain performance. The result also shows that information sharing provides more benefits to the supplier than to the retailers.

When DP = SDT, the performance differences between different levels of information sharing are much higher than when DP = SIT. Furthermore, both OIS and DIS produce significant cost savings relative to NIS when DP = SDT. Under all other DPs, DIS usually does not perform significantly better than NIS. This unique phenomenon is caused by a decreasing trend in demand. When demand is decreasing, initial demand is high and there is not sufficient capacity to satisfy the demand during the early periods of the simulation run. Backorders from the early periods therefore have to be satisfied first in later periods. This also causes insufficient capacity to satisfy demand in later periods of the simulation run. Thus, making better use of capacity is more crucial for improving the performance of the entire supply chain when retailers face decreasing trends. Because of this, when retailers share demand information with the supplier, the supplier can dramatically improve capacity utilization, which is also why DIS performs dramatically better than NIS.

The results in Tables 4–7 clearly show that the DP can significantly influence the performance of the forecasting model and moderate the impact of the forecasting models on the value of IS in a supply chain. In general, both the DP and FM significantly influence the value of IS. More accurate forecasts will enhance the value of IS. When information is not shared between the supplier and the retailers, more accurate forecasts may not result in a better system performance. The results indicate that there is a need to select forecasting models and proper level of IS jointly in order to improve supply chain performance. This result also indicates that IS is very beneficial for the supplier under all DPs, but is not dramatically beneficial for retailers unless all retailers face demand with trends. These observations support Hypothesis 2.

Our results also indicates that information-sharing is most beneficial when the demand patterns show a decreasing tend.

5.3. The interaction between CT, FM and IS

ANOVA results in Table 2 show that at the 5% significance level, the three-way interaction $CT * FM * IS$ has significant effects on TC, TCS, TCR, and SLR, but has an insignificant effect on SLS. The performances of IS and FM are presented in Tables 8, 9, and 10 for the three levels of CT, respectively. Examination of the results in Tables 8–10 clearly shows that the impact of the forecasting model and information sharing is significantly influenced by the CT factor. Some of the key results are summarized below.

When CT is low, sharing planned order information (OIS) with the supplier results in significantly lower total costs for the supplier and for the entire supply chain over DIS and NIS. However, OIS results in higher total costs for the retailers. The differences between DIS and NIS are normally not significant. The reason that retailers' total costs increase for OIS when CT is low is that the retailers' service levels are already very high even without IS. Thus IS is not very helpful in improving service levels and reducing retailers' backorder costs. However, when there is OIS between the retailers and the supplier, the supplier service levels to the retailer are substantially improved and thus the supplier's backorder costs are reduced. At the same time, the retailers' inventory carrying costs increase as a result of the on-time delivery of the goods from the supplier. Total costs

Table 8
Performance of information sharing under different forecasting models when CT = LOW

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	132	2–3	307	2–3	100	1–2	72.80	2–3	99.77	2–3
	DIS	132	2–3	307	2–3	100	1–2	72.80	2–3	99.78	2–3
	OIS	100	1	100	1	112	3	99.67	1	100.00	1
NAV	NIS	147	2–3	367	2–3	111	1–2	68.97	2–3	99.30	1–3
	DIS	147	2–3	367	2–3	111	1–2	68.99	2–3	99.30	1–3
	OIS	137	1	253	1	120	3	81.28	1	99.37	1–3
SMA	NIS	139	2–3	313	2–3	112	1–2	72.86	2–3	99.56	1–3
	DIS	139	2–3	313	2–3	112	1–2	72.86	2–3	99.56	1–3
	OIS	123	1	159	1	123	3	93.45	1	99.61	1–3
DES	NIS	138	2–3	312	2–3	112	1–2	72.82	2–3	99.50	1–3
	DIS	138	2–3	312	2–3	112	1–2	72.82	2–3	99.50	1–3
	OIS	122	1	157	1	123	3	93.32	1	99.54	1–3
NTW	NIS	138	2–3	305	2–3	113	1–2	73.35	2–3	99.82	1–3
	DIS	138	2–3	305	2–3	113	1–2	73.35	2–3	99.82	1–3
	OIS	120	1	148	1	124	3	94.58	1	99.85	1–3
WIN	NIS	138	2–3	304	2–3	113	1–2	73.55	2–3	99.78	2–3
	DIS	138	2–3	304	2–3	113	1–2	73.55	2–3	99.78	2–3
	OIS	120	1	144	1	124	3	95.15	1	99.84	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

Table 9
Performance of information sharing under different forecasting models when CT = MEDIUM

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	163	2–3	243	2–3	146	2–3	67.27	2–3	97.37	2–3
	DIS	161	2–3	240	2–3	142	2–3	67.29	2–3	97.40	2–3
	OIS	100	1	100	1	100	1	93.11	1	98.29	1
NAV	NIS	168	2–3	273	2–3	152	2–3	63.52	2–3	97.26	2–3
	DIS	166	2–3	271	2–3	149	2–3	63.53	2–3	97.28	2–3
	OIS	140	1	195	1	128	1	74.96	1	97.65	1
SMA	NIS	166	2–3	254	2–3	151	2–3	67.40	2–3	97.50	2–3
	DIS	161	2–3	247	2–3	142	2–3	67.44	2–3	97.53	2–3
	OIS	115	1	132	1	106	1	86.95	1	98.12	1
DES	NIS	166	2–3	253	2–3	151	2–3	67.47	2–3	97.42	2–3
	DIS	166	2–3	252	2–3	150	2–3	67.47	2–3	97.43	2–3
	OIS	118	1	136	1	112	1	86.77	1	98.00	1
NTW	NIS	165	2–3	250	2–3	149	2–3	67.89	2–3	97.73	2–3
	DIS	157	2–3	240	2–3	135	2–3	67.96	2–3	97.81	2–3
	OIS	112	1	125	1	104	1	88.15	1	98.40	1
WIN	NIS	165	2–3	249	2–3	150	2–3	68.18	2–3	97.70	2–3
	DIS	162	2–3	246	2–3	144	2–3	68.21	2–3	97.72	2–3
	OIS	113	1	124	1	106	1	88.60	1	98.35	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.

[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.

[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

Table 10
Performance of information sharing under different forecasting models when CT = HIGH

Independent variables		Dependent variables									
		TC		TCS		TCR		SLS		SLR	
FM	IS	RTC[a]	RANK[c]	RTCS[a]	RANK[c]	RTCR[a]	RANK[c]	SLS[b]	RANK[c]	SLR[b]	RANK[c]
ACT	NIS	137	3	156	3	133	3	61.19	2–3	95.15	2–3
	DIS	126	2	146	2	120	2	61.38	2–3	95.30	2–3
	OIS	100	1	100	1	101	1	86.06	1	96.45	1
NAV	NIS	137	3	165	3	132	3	57.64	2–3	95.40	2–3
	DIS	132	2	160	2	125	2	57.74	2–3	95.47	2–3
	OIS	116	1	131	1	112	1	68.23	1	95.91	1
SMA	NIS	137	3	161	3	132	3	61.40	2–3	95.57	2–3
	DIS	123	2	147	2	115	2	61.64	2–3	95.73	2–3
	OIS	102	1	108	1	100	1	79.69	1	96.22	1
DES	NIS	136	3	159	3	132	3	61.47	2–3	95.59	2–3
	DIS	129	2	152	2	123	2	61.57	2–3	95.67	2–3
	OIS	105	1	110	1	104	1	79.96	1	96.19	1
NTW	NIS	136	3	160	3	132	3	61.77	2–3	95.75	2–3
	DIS	123	2	147	2	116	2	62.00	2–3	95.90	2–3
	OIS	101	1	107	1	100	1	81.27	1	96.41	1
WIN	NIS	136	3	159	3	132	3	62.14	2–3	95.79	2–3
	DIS	125	2	148	2	118	2	62.34	2–3	95.92	2–3
	OIS	103	1	108	1	103	1	81.66	1	96.42	1

[a] RTC, RTCS, and RTCR represent relative total costs of the entire supply chain, the supplier and retailers, respectively. The lowest total cost among different values of the independent variables is set at 100. The relative total costs of the other values of the independent variables are obtained by dividing the lowest total costs into the total costs of the specific conditions.
[b] SLS and SLR represent service levels for the supplier and retailers, respectively. It is the percentage of the orders or demands filled from on-hand inventory.
[c] RANK represents rank of the values of an independent variable obtained using Duncan's multiple range tests with a significance level of 5%.

to the retailers thus increase by sharing information with the supplier.

When CT is medium or high, OIS performs better than sharing only the net requirements information (DIS), and DIS, in turn, performs better than no information sharing (NIS) for all three total costs under all conditions. When CT is medium, OIS values relative to NIS (from 20% for NAV to 63% for ACT) are much higher than when CT is high (from 18% for NAV to 37% for ACT) or when CT is low (from 7% for NAV to 32% for ACT). When CT is medium or high, there is usually not enough capacity to satisfy demand in most periods. Under these conditions, making better use of capacity is more critical to improve all round performance. IS can help the supplier better utilize its capacity to meet retailer demand and reduce backorder costs for both the supplier and the retailers. This helps them to reduce costs and improve service levels. The highest values of IS with a medium rather than the highest level of CT are due to the fact that the supplier has more room to improve capacity utilization with IS when CT is lower.

CT also significantly influences the performance of the forecasting models and their impact on IS values. When CT is low (Table 8), the improvement in total costs under OIS over NIS is relatively small under all forecasting models. Under OIS, total costs within the supply chain are reduced by 37% by knowing the demand with certainty (FM = ACT) versus using the Naïve model to make demand forecasts (FM = NAV). More accurate forecasts also enhance the value of IS (32% improvement of OIS versus NIS for FM = ACT, but only 7% for corresponding improvements for FM = NAV). Comparison of costs saved by sharing information with costs saved by using different forecasting models, shows us that selecting the right forecasting models can help the supply chain to achieve more benefits than if information is shared. Combining improvements in forecasting accuracy and IS will produce the best results.

When CT is high (Table 10), differences in performance (TC, TCS, and TCR) produced by different forecasting models are reduced (16% difference in TC between the best and the worst when IS = OIS, and 1% difference when IS = NIS). However, the cost savings achieved through IS are much higher and the more accurate forecast makes IS more valuable. For example, costs saved by OIS relative to NIS are 37% and 18% for FM = ACT and NAV, respectively. This is because the supplier usually has to use most of its capacity to produce since the capacity is very tight. Thus whether the forecast is accurate is not very important for improving capacity utilization and, subsequently, the performance of the supply chain. IS will, however, allow the supplier to better utilize its capacity.

When CT is medium (Table 9), sharing information can produce even greater savings (total cost savings of OIS relative to NIS range from 20% for FM = NAV to 63% for FM = ACT). This is because the supplier has more room to improve capacity utilization when information is shared by the retailers. Furthermore, improvements in forecasting accuracy can also help to improve supply chain performance. Therefore, both selecting the right forecasting model and IS are important for improving the supply chain performance. This result shows that IS is very beneficial for the supplier under all forecasting models and CT, but is beneficial for the retailers only when CT is medium or high.

Overall the results in Tables 8–10 indicate that the impact that the forecasting model has on the value of IS differs according to CT. These observations support Hypothesis 3.

6. Conclusions

This study investigates the impact of forecasting models on supply chain performance and the value of sharing information in a supply chain with one capacitated supplier and multiple retailers under demand uncertainty. Through comprehensive simulation experiments and subsequent analysis of the simulation outputs, we made the following important findings.

Information sharing can significantly influence the performance of the supply chain. Sharing future order information with the supplier is more beneficial than sharing only future demand information. Total cost savings for the entire supply chain are substantial under most conditions.

The value of information sharing is significantly influenced by the demand pattern, the forecasting model used and capacity tightness. The more accurate the forecast model, usually the larger the value of information sharing. Information sharing can achieve greater improvements in supply chain performance when retailers face identical demand with trends and/or with medium capacity tightness. The improvement in total costs for the entire supply chain can be as high as 60% under some conditions.

The benefits to different parties in the supply chain may be quite different under different conditions. The supplier can usually improve its total costs and service level dramatically through information sharing under all conditions. However, the total costs and service level for retailers may even worsen when they share information with the supplier under some demand conditions when capacity tightness is low. Therefore, the supplier must provide some incentives to the retailers under these conditions, or retailers may not be willing to participate in an information-sharing project.

These findings help us to understand the benefits of information sharing in supply chain and have the potential to encourage companies to share information with their supplier. The magnitude of cost savings can help companies weigh the cost of sharing information against the benefits of sharing information with the supplier. The findings of this study can also help supply chain managers reduce the negative impact of forecasting errors by using the proper forecasting model in combination with information sharing.

Although the findings from this simulation study provide important insights into information sharing between the supplier and retailers in a supply chain, there are also limitations. The following are the limitations of the study and possible avenues for future research.

In this study we only investigated a piece of the entire supply chain which consists of four retailers and one capacitated supplier dedicated to only a single product. There are many possible supply chain structures, for example, multiple supplier–single retailer, multiple supplier–multiple retailer, tri-level supply chains involving supplier–manufacturer–retailers. It will be useful to investigate the impact of information sharing on supply chain performance under other supply chain paradigms with more complicated structures.

This study only examined three kinds of information to be shared between the supplier and the retailers (namely, no information, demand or order information). Other types of information (for example, inventory levels, capacity, planned production, etc.) can also be shared. Future research should propose and evaluate these other modes of sharing information.

The cost structure (ordering or setup costs, transportation costs, inventory costs and backorder costs) used in this study only represents one special case. Examination of the impact of cost structures on the effect of information sharing in a supply chain may provide further insights on the value of information sharing.

In this study we assume that the supplier uses a capacitated lot-sizing rule to make its production decisions and that retailers use EOQ to make their inventory decisions. Investigation of the impact of alternative production and inventory policies on the value of information sharing can also be a fruitful area for future research.

This study only investigated the impact of a few simple time series forecasting models. It will be interesting to look at how other forecasting models will influence the performance of the system and the value of information sharing.

This study focused on the impact of forecasting models and information sharing on the cost savings that can be achieved by the supplier and retailers in their production inventory systems. We did not include the actual costs of sharing the information and we did not consider the impact of sharing information on revenue. Future studies should explore the impact of information sharing on both costs and revenues to obtain a more complete understanding of the impact of information sharing.

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