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Forecasting errors and the value of information sharing in a supply chain

XIANDE ZHAO†* and JINXING XIE‡

The paper investigates the impact of forecasting errors and information sharing on the performance of a supply chain. It also examines the impact of forecasting errors on the value of information sharing between retailers and a supplier. Analyses of the simulation outputs show that while information sharing can bring tremendous benefits to the supplier and the entire supply chain, it hurts the retailers under most conditions. Demand pattern and forecasting error distributions faced by the retailers significantly influence the magnitudes of the cost savings as a result of information sharing. The expected bias in forecast errors has a much more significant impact on supply chain performance and the value of information sharing than the standard deviation of forecasting errors and its pattern of deterioration over time. A slight positive bias in the retailer's forecast can actually increase the benefit of sharing information for the supplier and the entire supply chain. However, it can also increase the cost for retailers. The demand pattern faced by retailers also significantly influences the impact of forecasting accuracy on the value of the information sharing. These findings will motivate companies to share information, and will help to design incentive schemes to encourage information-sharing and justify investment in information-sharing projects. The findings can also be used to minimize the negative impact of forecasting errors on supply chain performance.

1. Introduction

Global supply chain management (GSCM) has become a very popular topic in recent years because it enables business corporations to improve customer services and at the same time reduce costs. GSCM has become one of the most popular approaches for enhancing the competitiveness of business enterprises in today's highly competitive environment, having regard to the coordination of products and information flows among suppliers, manufacturers, distributors, retailers and customers. In order that trading partners can successfully coordinate various activities in the supply chain, they have to share information with each other.

Modern information technology has provided a means to enable the sharing of information among different parties in a supply chain. However, there are often costs involved in setting up the appropriate system or channel. Many companies are reluctant to share information with their trading partners because they are unable to see how doing so would benefit them. Some even fear that their trading partners will take unfair advantages over them. In order for them to share information, it is necessary that they see how much they can gain by doing so. Estimating the magnitude of the benefits of sharing information to the different parties may help these

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parties design an incentive system that can have the effect of motivating their trading partners to share information. For these reasons, there is a real need to evaluate the magnitude of cost savings that can be achieved through information sharing.

Another factor that can significantly influence supply chain performance is forecasting accuracy. When retailers forecast demand using different models, the accuracy of the forecasts can differ dramatically depending on the market environment and how much effort the retailers put into their forecasting process. Retailer forecasting accuracy can significantly influence the quality of the replenishment decisions that they make, which, in turn, will influence the production and transportation decisions made by the supplier and, consequently, the performance of the entire supply chain. The accuracy of their forecasts can also influence the benefits of sharing information. Intuitively, as forecasting accuracy deteriorates as retailers forecast further into the future, the forecasts and the corresponding inventory decisions made by the retailers also become less reliable. The value of the information that retailers share with the supplier can, therefore, also decrease.

The purpose of this paper is to investigate the impact of forecasting error distribution faced by retailers with regard to the performance of a supply chain and the magnitude of the cost savings that can be achieved through information sharing. It will also examine how demand patterns faced by retailers influence the impact of forecasting error distribution on the value of information. The findings will help companies understand how great the benefits of sharing information under different conditions can be and how forecasting accuracy can influence the benefits of sharing information. Armed with knowledge of this kind, companies will be equipped to make more effective decisions when selecting information-sharing methods and when attempting to minimize the negative impact of demand uncertainty on supply chain performance.

The following sections will present a review of the related literature, which will be followed by a discussion of the simulation procedure, the experimental design and the research hypotheses. Subsequently, the results of the statistical analyses will be presented. The conclusion will summarize the major findings and contributions and will indicate some possible directions for future research.

2. Literature review

Many researchers have investigated issues relating to the design and management of supply chains. Among these demand distortions along a supply chain and the impact they have on the performance of a supply chain are a frequent topic of research. Lee *et al.* (1997) investigated the demand variability amplification along a supply chain from the retailers to the distributors. They called this amplification effect the bullwhip effect and identified four major causes. They proved mathematically that demand variation was amplified when orders were passed from retailers to the supplier. Chen *et al.* (2000a) quantified the bullwhip effect using an analytical model. They demonstrated that the variance of orders was always higher than the variance of demand, and that the magnitude of the variance was significantly influenced by the number of observations (N) used in the moving average model, the lead-time between the retailer and the manufacturer (L) and the correlation parameter (ρ) in the demand function. Chen *et al.* (2000b) examined the impact of exponential smoothing forecasts on the bullwhip effect and compared the results obtained using the exponential smoothing forecasting model with the results obtained using the moving average model. They found that reducing ordering lead-times and using more demand information in constructing the demand forecast could decrease the bullwhip effect. They also found that negatively correlated demand could lead to a greater increase in order variability than could positively correlated demand, and that a retailer forecasting a demand with a linear trend would receive more variable orders than a retailer forecasting an i.i.d. demand.

Most existing studies on the bullwhip effect focus on distortion in demand information as one proceeds upstream in the supply chain. Although these studies help us to gain insights into variations and distortions in order quantities, they do not allow for evaluation of the impact of the bullwhip effect on system performance. Metters (1997) studied the impact of the bullwhip effect on a company's profitability by establishing an empirical lower bound on the excessive cost as a result of the bullwhip effect. He found that the business environment of the firm could significantly influence the financial impact of bullwhip effect on the firm. He demonstrated that eliminating the bullwhip effect could increase product profitability by 10–30% under some conditions.

Although Metters demonstrated the financial significance of the bullwhip effect for a firm's performance, it did not consider the interaction between the retailer's inventory replenishment decisions and the supplier's production decisions. This study did not include the retailer; it considered only one supplier with a fixed production capacity and a demand with different variations. Demand was not based on the retailer's orders and ordering costs, transportation costs and production set-up costs were not considered.

Our review of the literature indicates that most studies in the supply-chain area made many assumptions in an attempt to solve related problems analytically. While these studies help practitioners understand the basic phenomena, they do not provide guidelines that are sufficient to help practising managers improve system performance. Computer simulation has been used to study the more practical issues in supply chain management. Using a computer 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. They found that the operational benefits associated with VMI to be very compelling. They also showed that the VMI approach greatly reduced inventories for all participants in the supply chain without compromising service. However, they implemented VMI by reducing ordering frequency from the retailers to the supplier and did not measure the benefits in term of cost.

Bhaskaran (1998) did a simulation study at General Motors Corporation and found that the Kanban systems that do not generate meaningful forecasts for suppliers can cause considerable degradation of schedule stability. She showed three typical profiles of the rate at which forecast deviation accelerates as forecasts go further into the future: constant rate, decreasing rate and increasing rate.

Although very few studies have examined the impact of forecasting errors on the performance of a supply chain, and while simulation has not been used much in supply chain studies, a significant number of simulation studies have been performed to examine the impact of forecasting errors on the performance of material requirements planning (MRP) systems. Biggs and Campion (1982) first investigated the impact of forecasting errors bias on MRP system performance and showed bias of forecasting errors to have a significant impact on the performance of a production and inventory system. The study demonstrated that over-forecasting could reduce the cost of MRP systems.

Lee and Adam (1986) investigated the impact of the bias and standard deviation of forecasting errors on the performance of multiple-stage MRP systems and the relative performance of lot-sizing rules. They found that both bias and the standard deviation of the forecasting errors had a significant impact upon MRP system performance. However, the impact of forecasting errors upon the system's performance was dependent on the MRP structure. It was also found that moderate positive bias (10–30%) reduced the total cost of the MRP systems studied. Lee *et al.* (1987) studied the relationship between the total cost of MRP systems and four traditional forecasting error measures, i.e. bias, standard deviation, mean absolute deviation (MAD) and mean square errors (MSE). They found that bias outperformed the other three forecasting error measures in explaining total cost variations for MRP systems with a bill of material level of six using any lot-sizing rules. MSE and MAD explained a high proportion of total cost variations for the MRP systems with a bill of material level equal to three using certain lot-sizing rules. In contrast, a much lower standard deviation explained variation in total cost for any MRP structures or lot-sizing rules.

Ritzman and King (1993) studied the relative significance of forecasting errors in multistage manufacturing. They found that the mean forecasting error (bias) had a significantly higher impact on inventory level and past-due demand than forecasting error variability. They also found that many other factors have a much greater impact on both inventory level and past-due demand than the forecasting error measures. These factors include lot-sizing rules, percentage of special products and buffer stock levels.

Zhao and Lee (1993) studied the impact of master production schedule freezing parameters on the performance of MRP systems using double exponential smoothing (DES) and Winters' model (WIN). They found that although Winters' model resulted in lower bias and standard deviation of forecasting errors, it resulted in higher total cost and schedule instability in the MRP operating settings that they used. Zhao *et al.* (1995) studied the impact of forecasting models on the performance of lot-sizing rules and 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 in forecasting errors. At the same time, the forecasting errors often have a significant impact on the relative performance of the lot-sizing rules and the MPS freezing parameters.

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

3. Simulation model

We used a simulation model here rather than analytical approaches because we wanted to capture the interactions between the supplier's decisions and the retailers' decisions under an environment with capacity constraints and demand uncertainty. The simulated supply chain consists of one supplier and four retailers. The supplier is assumed to be a manufacturer with a fixed production capacity to produce a single product for the retailers. The lead-time needed to produce the product is assumed to be zero if the required production capacity is available. Production will be delayed until the next period if there is not sufficient capacity to produce the product in the current period.

All retailers are assumed to have identical demand distributions with the same average demand of 1000 units per period for each retailer. The retailers make demand forecasts for future periods in their planning horizon and make their inventory replenishment decisions using the economic ordering quantity rule based on their demand forecasts.

Retailer planning horizons are eight times their natural ordering cycle, and replanning periodicity is one period. For example, if the natural ordering cycle for the retailer is four periods, the retailer will forecast a demand for 32 periods into the future and plan for replenishment activities for the following 32 periods in each replanning cycle. Once they have made their inventory replenishment decisions, they will place the first order with the supplier. Depending on the level of information sharing between the supplier and the retailers, the supplier may receive additional information from the retailers. In the case of no information sharing (NIS), retailers only send the first order to the supplier and share no other information. In the case of demand information sharing (DIS), the retailers inform the supplier of their projected future net requirements in their planning horizon based on current inventory and future forecasts. In the case of planned order information sharing (OIS), the retailers also inform the supplier of its future order plans based on current inventory, future forecast and rules for determining order quantity.

The supplier receives the first orders in the retailers' planning horizons and the information shared by the retailers, then makes production decisions using a capacitated lot-sizing rule as proposed by Chung and Lin (1988). In this study, it is assumed that the capacity absorption for each unit of product is equal to one. That is to say, one unit of resource is required by the supplier to produce exactly one unit of product. This assumption will not cause the generality of the conclusion to be lost as demand for each product can always be measured by the units of the resource needed to produce the product. Available capacity is assumed to be at a constant level during the entire simulation horizon and the average capacity utilization is set at 80%.

After the current period's production finishes at the end of each period, the supplier makes delivery decisions based on available inventory and customer orders. The supplier fulfils each retailer's order (plus backorders if any) if on-hand inventory is sufficient to fulfil all retailers' orders and backorders. If on-hand inventory is insufficient, each retailer will be allocated a quota proportional to its order (plus backorder if any) and any shortages will become backorders. The shipment will arrive at the retailers via truck after the transportation lead-time. The truckload is assumed to be large enough so that a single truck can complete a shipment to any retailer in any period.

The party to whom transportation costs will be charged depends on whether there is an order placed by the retailer in that period. When there is, the retailer will pay the transportation costs of the current period's shipment regardless of whether a proportion of the shipment is used to satisfy the backorder of previous orders. However, when there is no order placed by the retailer in that period, the shipment to the retailer is used only to satisfy the backorders of previous orders, and the supplier will pick up the bill for making the shipment.

The transportation costs per truck from the supplier to the retailers as used in this study are adopted from a real case. Whenever a retailer places an order to the supplier, a fixed order processing cost ($100 per order in this study) is incurred in addition to the transportation costs. Therefore, the retailer's ordering cost as used in making inventory replenishment decisions is the sum of the transportation costs and the fixed-order processing costs. The supplier's production set-up costs are assumed to be $1000 per set-up. The inventory holding costs (h) per unit per day for the supplier and retailers are designed in such a way that the natural ordering cycles for the retailers and the supplier cover 4 days. This approach of designing the cost structure has been used in previous studies (Zhao and Lee 1993, Zhao *et al.* 1995). The cost parameters used in this study are within the range of parameters used by Ebert and Lee (1995).

When the supplier is unable to fulfil a retailer's orders on time or when a retailer is unable to meet demand on time, a backorder cost will be incurred. Assessment of the backorder cost is a little difficult. The backorder cost should indicate the loss of goodwill and the potential future loss of profit as a result of customer dissatisfaction caused by the backorder. In this study, backorder costs per unit per day for both the supplier and the retailers are 10 times their corresponding unit inventory holding cost per day. The cost structures (order processing costs, transportation costs, inventory costs and backorder costs for the retailers; set-up costs, inventory costs and backorder costs for the supplier) are shown in table 1. The cost parameters are within the range of the parameters used in Ebert and Lee (1995).

The above process is repeated until ordering, production and delivery decisions are developed for all 200 periods. After the entire simulation run is completed, the inventory costs, order processing or set-up costs, backorder costs, transportation costs and total cost will be calculated for the retailers and the supplier. The aggregate total cost for the entire supply chain will also be calculated and used as the performance measure of the supply chain.

Supplier/retailer	Supplier	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Order processing costs ($/order) (transportation costs excluded)	1000 (set-up costs)	100	100	100	100
Transportation costs ($/truck)	N/A	450	255	331	553
Natural ordering cycle (periods)	4	4	4	4	4
Backorder costs ($/unit/period) (in terms of inventory carrying cost per unit per period[1])	10	10	10	10	10

[1]Inventory holding costs ($/unit/period) can be calculated by using the EOQ formula with the natural ordering cycle and the average demand.

N/A, not applicable.

Table 1. Cost structure with one supplier and four retailers.

To minimize the termination effect, the length of the simulation run is selected to be 200 periods, and the results from the first 50 periods and the last 10 periods are excluded from performance measure calculation. Therefore, the final performance measures are calculated based on 140 simulation periods (periods 50 to 189). Furthermore, to avoid possible backorders for the retailers during the beginning periods due to transportation lead-time, sufficient initial inventory is assumed for each retailer. In this study, we set the initial inventory for the ith retailer at $(1+i)*1000$ ($i=1$–4). The second part of the initial inventory ($i*1000$ units) is used to give the different retailers different initial inventories.

4. Experimental design

4.1. *Independent variables*

The independent variables and the values used in the simulation experiment are shown in table 2 and are described below.

4.1.1. *Retailer demand pattern (DP)*

To investigate how demand pattern influences the value of information sharing and the impact of forecasting errors on the value of information sharing, the actual demand patterns faced by the retailers are varied and generated using the following formula:

$$\text{Demand}_t = \text{base} + \text{slope} \times t + \text{season} \times \sin\left(\frac{2\pi}{\text{Season Cycle}} \times t\right) + \text{noise} \times \text{snormal}(), \tag{1}$$

where Demand_t is the demand in period t ($t = 0, 1, 2, \ldots, 199$), snormal() is a standard normal random number generator and SeasonCycle $= 7$ in this study. The other parameters (base, slope, season, noise) are characteristic parameters for demand generators. The base is selected in such a way to ensure that average demand for the 140 simulation periods (periods 50 to 189) is 1000. To avoid the possibility of generating negative demand, we restricted the standard normal random variable to values from the range of -3.0 to $+3.0$ only. In this study, we used three different demand patterns representing demand with seasonality but no trend (SEA), demand with an increasing trend and seasonality (SIT) and demand with a decreasing trend and seasonality (SDT). The demand characteristic parameters are shown in table 3.

Variable number	Variable name	Label	Number of levels	Values
1	retailer's demand patterns	DP	3	SEA, SIT, SDT
2	forecasting error bias	EB	4	50,0,50,100
3	forecasting error deviation	ED	3	0,50,200
4	increase rate	IR	3	LIN, CVX, CCV
5	information sharing	IS	3	NIS, DIS, OIS

Table 2. Summary of the independent variables.

Demand generator	Base	Slope	Season	Noise
SEA	1000.0	0	200	100
SIT	761.0	2	200	100
SDT	1239.0	2	200	100

Table 3. Demand patterns.

4.1.2. *Forecasting error distribution*

To examine the impact of forecasting error distribution on system performance and the value of information sharing, it is assumed that retailer's forecasting errors follow normal distributions. The forecasts that the retailers make will be equal to the demand plus the forecasting errors. This approach has been used in a number of studies (Biggs and Campion 1982, Lin and Krajewski 1992, Lee and Adam 1996, Bhaskaran 1998). The forecasting errors distributions are characterized by three parameters: the mean (bias) of forecasting errors (EB), the initial standard deviation (ED) that measures forecast variability and the rate of increase (IR) of forecast deviation over time. Hence, the demand forecast made at period t_0 for a period t ($t \geq t_0$) is generated according to the following formula:

$$\text{Forcast}_t = \text{Demand}_t + \text{EB} + \text{ED} \times \text{IR}(t - t_0 + 1) \times \text{snormal}(), \tag{2}$$

where Demand_t is the demand in period t ($t = 0, 1, 2, \ldots, 199$) as given in equation (1) and snormal() is a standard normal random number generator. EB is set at -50, 0, $+50$, $+100$, while ED is set at 0, 50, 200. Borrowing the idea from Bhaskaran (1998) discussed above, we selected three increase rate patterns (IR) for forecast deviation: linear (LIN, a constant rate), concave (CCV, an increasing rate) and convex (CVX, a decreasing rate). The three different patterns of change are demonstrated in figure 1.

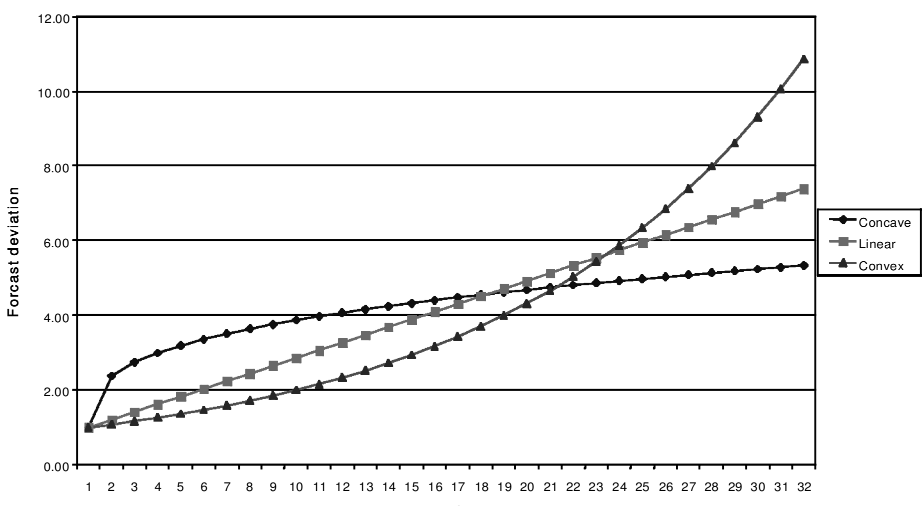


Figure 1. Patterns of increasing rate of forecast deviation.

4.1.3. *Information sharing (IS)*

Information sharing refers to the degree to which the retailers share demand or order information with the supplier. Three cases will be examined: no information sharing (NIS), demand information sharing (DIS) and order information sharing (OIS). The way that the information is shared and how the supplier uses the information in each case has been discussed above.

4.2. *Dependent variables*

The following criteria are used as the dependent variables of the experimental design.

- Total cost for retailers (TCR), which is the sum of the ordering costs (including transportation costs), inventory carrying costs and backorder costs.
- Total cost for the supplier (TCS), which is the sum of the set-up costs, transportation costs (for backorder deliveries), inventory carrying costs and the backorder costs.
- Total cost for the entire supply chain (TC), which is the sum of the TCR and TCS, minus the backorder costs paid from the supplier to the retailers. We make this subtraction because TC is only an internal cost within the supply chain and is not actually incurred.

5. Research hypotheses

The output from the simulation experiments will be analysed to test the following research hypotheses.

Hypothesis 1: Forecasting error distribution will significantly influence supply chain performance. Higher forecasting errors (EB or ED) will result in a worse performance.

Hypothesis 2: Forecasting error distribution will significantly influence the value of information sharing. Higher forecasting errors (EB or ED) will reduce the benefits of information sharing.

Hypothesis 3: Demand pattern faced by the retailer will significantly influence the impact of forecasting error distribution on the values of information sharing. When the demand has either an increasing or a decreasing trend, the forecasting error distribution will have a greater impact on supply chain performance and the value of information sharing.

6. Results

For each combination of the independent variables, the simulation ran with 20 replications. This number of replications was selected to provide 95% confidence that the true mean would be within 1% of the estimated mean. The output from the simulation experiments was analysed using the SAS analysis of variance (ANOVA) procedure and Duncan's test. Residual analyses were performed, and suggested transformations were made to the dependent variables using SAS. Selected ANOVA results are presented in table 4. Results of the Duncan's test are presented in table 5. These results, discussed around the research hypotheses, are presented below.

Dependent variables	TC			TCS†			TCR‡		
Source	R^2	F	$Pr > F$	R^2	F	$Pr > F$	R^2	F	$Pr > F$
DP	0.0101	580.15	< 0.0001	0.0005	26.13	< 0.0001	0.0029	232.56	< 0.0001
EB	0.3849	14673.40	< 0.0001	0.0056	213.58	< 0.0001	0.5031	26604.20	< 0.0001
ED	0.0102	580.70	< 0.0001	0.0128	732.72	< 0.0001	0.0083	661.26	< 0.0001
IR	0.0009	53.62	< 0.0001	0.0008	43.83	< 0.0001	0.0004	30.31	< 0.0001
IS	0.1937	11077.90	< 0.0001	0.6656	38010.20	< 0.0001	0.2693	21357.20	< 0.0001
DP*EB	0.0418	795.95	< 0.0001	0.0065	123.45	< 0.0001	0.0037	97.27	< 0.0001
DP*ED	0.0018	50.53	< 0.0001	0.0005	14.81	< 0.0001	0.0000	1.12	0.3466
DP*IR	0.0000	1.25	0.2887	0.0000	0.78	0.5402	0.0000	0.56	0.6885
DP*IS	0.0085	242.84	< 0.0001	0.0018	50.12	< 0.0001	0.0021	82.19	< 0.0001
EB*ED	0.1093	2082.88	< 0.0001	0.0254	483.88	< 0.0001	0.0703	1859.05	< 0.0001
EB*IR	0.0007	12.62	< 0.0001	0.0002	3.04	0.0057	0.0005	14.29	< 0.0001
EB*IS	0.1213	2312.74	< 0.0001	0.1797	3421.34	< 0.0001	0.0897	2370.52	< 0.0001
ED*IR	0.0011	32.76	< 0.0001	0.0007	20.06	< 0.0001	0.0019	75.07	< 0.0001
ED*IS	0.0052	149.54	< 0.0001	0.0098	280.14	< 0.0001	0.0002	7.09	< 0.0001
IR*IS	0.0000	0.86	0.4866	0.0001	3.31	0.0102	0.0001	3.22	0.0118
DP*EB*ED	0.0030	28.30	< 0.0001	0.0016	15.21	< 0.0001	0.0006	8.07	< 0.0001
DP*EB*IR	0.0001	0.53	0.8940	0.0001	0.65	0.7969	0.0000	0.51	0.9076
DP*EB*IS	0.0314	299.65	< 0.0001	0.0113	107.26	< 0.0001	0.0032	42.08	< 0.0001
DP*ED*IR	0.0000	0.47	0.8780	0.0000	0.60	0.7790	0.0000	0.49	0.8644
DP*ED*IS	0.0014	20.65	< 0.0001	0.0008	11.65	< 0.0001	0.0001	1.75	0.0825
DP*IR*IS	0.0000	0.40	0.9226	0.0000	0.27	0.9756	0.0000	0.33	0.9535
EB*ED*IR	0.0010	9.73	< 0.0001	0.0005	5.04	< 0.0001	0.0020	26.41	< 0.0001
EB*ED*IS	0.0159	151.90	< 0.0001	0.0190	180.51	< 0.0001	0.0015	20.11	< 0.0001
EB*IR*IS	0.0003	2.79	0.0008	0.0002	1.99	0.0210	0.0001	1.13	0.3324
ED*IR*IS	0.0001	0.76	0.6411	0.0002	2.49	0.0108	0.0001	1.52	0.1441
DP*EB*ED*IR	0.0002	0.72	0.8325	0.0001	0.52	0.9751	0.0001	0.43	0.9929
DP*EB*ED*IS	0.0024	11.28	< 0.0001	0.0018	8.48	< 0.0001	0.0006	4.02	< 0.0001
DP*EB*IR*IS	0.0001	0.49	0.9812	0.0001	0.40	0.9958	0.0001	0.78	0.7690
DP*ED*IR*IS	0.0001	0.97	0.4916	0.0001	0.43	0.9745	0.0000	0.23	0.9993
EB*ED*IR*IS	0.0003	1.49	0.0594	0.0002	1.14	0.2913	0.0001	0.78	0.7704
DP*EB*ED*IR*IS	0.0003	0.68	0.9568	0.0002	0.46	0.9995	0.0001	0.48	0.9992

† Based on residual analysis and suggestion by SAS, inverse square root transformation of TCS (i.e. $1/\sqrt{(TCS)})$ was made to satisfy the assumptions of ANOVA.
‡ Based on residual analysis and suggestion by SAS, square transformation of TC (i.e. TCR^2) was made to satisfy the assumptions of ANOVA.

Table 4. Selected ANOVA results.

Dependent variables		Relative total cost (RTC)		Relative supplier total cost (RTCS)		Relative retailers total cost (RTCR)	
Source		RTC†	RANK‡	RTCS	RANK	RTCR	RANK
EB	50	105.0	2	103.2	4	104.0	2
	0	100.0	1	100.0	1	100.0	1
	50	106.8	3	102.2	3	107.8	3
	100	115.6	4	101.9	2	120.4	4
ED	0	100.0	1	100.0	1	100.0	1
	50	101.8	2	103.0	2	101.9	2
	200	101.9	3	106.4	3	102.7	3
IS	NIS	109.4	3	169.9	3	100.0	1
	DIS	106.5	2	141.7	2	106.0	2
	OIS	100.0	1	100.0	1	113.8	3
DP	SEA	101.5	2	100.2	1–2	101.1	2–3
	SIT	102.0	3	101.1	3	101.1	2–3
	SDT	100.0	1	100.0	1–2	100.0	1

† Values are the relative TC, TCS and TCR. The minimal cost among the different levels of an independent variable is set to 100, and the costs for other levels are set relative to the minimal cost.

‡ Ranking of the performance is based on the results of Duncan's test at the 5% significance level. Duncan's test was performed on the transformed data. The transformation is based on the suggestion by SAS as indicated in table 4.

Table 5. Duncan's grouping results.

6.1. *Impact of forecasting error distribution (EB, ED and IR) on the performance of the supply chain*

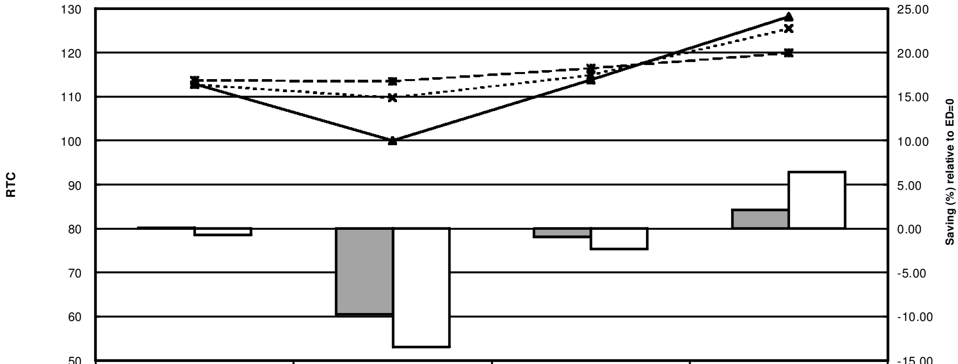
Table 4 shows that at the 5% significance level, both the expected bias (EB) and initial standard deviation (ED) parameters of the forecasting errors distribution have significant effects on all three dependent variables. The interaction effect between EB and ED is also significant according to all three dependent variables. Although the increase rate (IR) is also statistically significant, analyses show that its impact on system performance and the value of information sharing is much lower than for the other two forecasting error parameters. Therefore, we will not present our IR results.

The main effects of the EB and ED parameters are shown in table 5, where we can see that a higher standard deviation always results in a higher total cost for the supplier, the retailers and the entire supply chain. Therefore, reducing the variability in the forecasting errors will help to improve the performance of all parties in the supply chain. However, when the impact of expected bias (EB) is examined, the situation is somewhat different. Generally speaking, an unbiased forecast (EB $= 0$) will result in the lowest total cost for the supplier, the retailer and the entire supply chain. When there is a bias in the forecast, the costs for the retailers, suppliers and the entire supply chain all go up. A negative bias (EB $= -50$) results in the next lowest costs for the retailers and the entire supply chain, followed by a positive bias of 50. A positive bias of 100 results in the highest total supply chain cost and total cost for the supplier. This result indicates that a higher positive bias in the forecast will worsen the performance of the supply chain, and increase the costs for retailers. When a negative bias exists in the forecast, the forecast is lower than the actual demand. The retailers will use the initial inventory to meet the demand. Therefore, the initial inventory will be reduced, which will result in a lower inventory carrying cost for retailers. This is why a negative bias of 50 produces slightly lower costs for retailers (TCR) and the entire supply chain (TC) than a positive bias of 50.

For the supplier, a positive bias of 50 or 100 results in lower cost than a negative bias of 50. This is because when retailers over-forecast demand, they place larger orders with the supplier, who will try to produce more using the capacity available. Over-production in certain periods reduces the probability of shortages due to insufficient capacity, and thus reduces the backorder costs for the supplier.

To examine the effect of the interactions between the bias and standard deviation (EB*ED), relative total costs (RTC) under different combinations of ED and EB are shown in figure 2, which also shows the cost savings (positive) or increase (negative) for ED $= 50$ and 200, respectively, relative to ED $= 0$ by means of a histogram. From figure 2, one can see that when EB $= -50$, 0 or $+50$, a higher standard deviation will result in a higher total cost, as the higher variation in the forecast will produce higher backorder costs. However, when the bias $= 100$ the reverse is true, as the higher positive bias will lead to additional buffer stock in the supply chain, and thus backorder costs become less significant than inventory carrying costs. Analyses of the component costs for the supplier and retailers also show that a higher standard deviation (ED) leads to lower inventory carrying costs for the supplier, due to the higher lumpiness in the demand forecast. When the expected bias (EB) is 100, the inventory holding cost is the dominant component in the total cost, and thus a higher ED produces better performance.

Under all three levels of ED, total costs under a negative bias of -50 are larger than those under an unbiased forecast (EB $= 0$). When the bias is increased from 0 to $+50$, and then to $+100$, the total cost increases, but the magnitude of the increase in



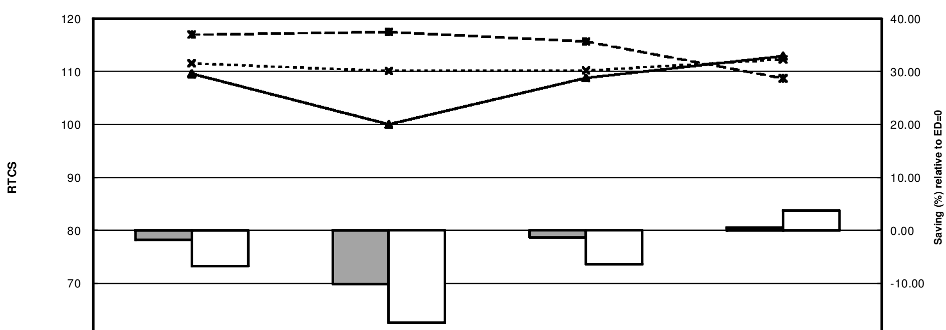
	-50	0	50	100
50	0.12	-9.77	-0.93	2.13
200	-0.71	-13.48	-2.32	6.44
0	113	100	114	128
50	113	110	115	125
200	114	113	116	120

EB

Figure 2. Relative total cost (RTC) versus expected bias (EB) and standard deviation (ED).

total cost is much lower when ED = 200 than the corresponding increases in total cost when ED = 0 or 50. This smaller increase in total cost is a result of an increased need for safety stock when ED is higher.

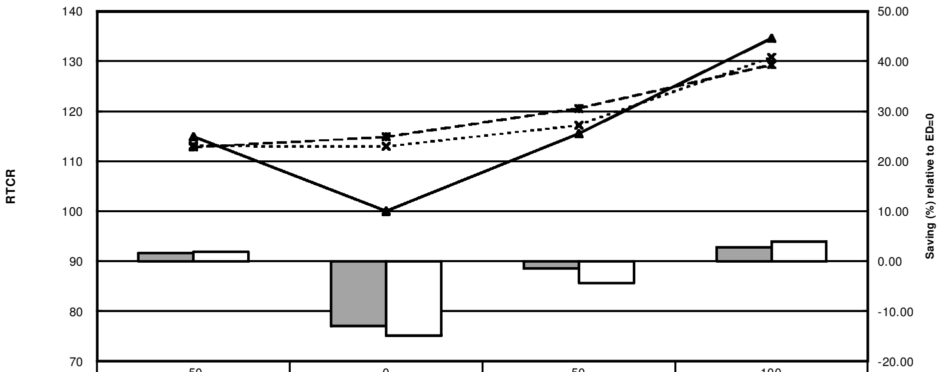
Figures 3 and 4 show the relative total costs for the supplier (RTCS) and retailers (RTCR) respectively. From these two figures, we can see that when ED = 0 or 50, total costs for both the supplier and retailers first decreases as EB increases from −50 to 0. They then increase when the bias increases further in the positive direction. When ED = 200, however, total cost for the supplier consistently decreases as EB increases from 0 to 100. Total cost for the retailers, on the other hand, increases as



	-50	0	50	100
50	-1.80	-10.09	-1.28	0.52
200	-6.73	-17.45	-6.32	3.73
0	110	100	109	113
50	112	110	110	112
200	117	117	116	109

EB

Figure 3. Relative total supplier cost (RTCS) versus expected bias (EB) and standard deviation (ED).



	-50	0	50	100
50	1.57	-12.92	-1.45	2.80
200	1.82	-14.85	-4.35	3.91
0	115	100	116	135
50	113	113	117	131
200	113	115	121	129

EB

Figure 4. Relative total retailer cost (RTCR) versus expected bias (EB) and standard deviation (ED).

the bias increases from -50 to $+100$, and the rate of increase becomes higher when the bias grows higher.

The differences in the relationship between TCS, TCR and EB under different standard deviations can be explained by the need for a higher level of safety stock to deal with the demand uncertainty in the supply chain. As ED increases, the forecast gains a higher level of uncertainty, which leads to a higher probability of stock-outs. When EB increases, the average forecast is adjusted upwards and thus introduces buffer stock into the system. This buffer stock helps to protect against the demand uncertainty in the supply chain. Furthermore, a higher positive bias leads to larger or earlier orders and thus helps to improve capacity utilization of the supplier. Therefore, the backorder cost for the supplier is substantially reduced. This is why the relative total cost for the supplier decreases as the bias increases under high standard deviation of the forecast error (ED = 200). For the retailers, however, the decrease in back order cost is less significant because of the initial inventory and the buffering effect of ordering for four periods each time (the natural ordering cycle is 4 days). The increase in inventory carrying cost as a result of the increase in bias becomes more dominant. Therefore, the relative total costs for the retailers increase as bias increases.

When the cost savings or increases of ED = 50 and 200 relative to ED = 0 in figures 3 and 4 were examined under different levels of expected bias (EB), we found that EB significantly influences the impact of ED on supplier and retailer costs. When EB = 0, the higher forecast uncertainty (ED = 50 or 200) results in much higher cost increases relative to no forecast uncertainty (ED = 0) for both the supplier and the retailers. When there is a positive bias of 100, higher uncertainty in the forecast can even help to reduce the total costs for both the supplier and retailers, due to the decreased inventory holding cost that results from the higher lumpiness in the demand forecast when the ED is higher.

Overall, the results presented above support the first hypothesis. The bias, the standard deviation of the forecasting errors, and their interactions, all significantly influence supply chain performance. When the bias is low (EB $= -50$, 0 and 50), a higher standard deviation in the error always results in a higher cost for both the supplier and the retailer. However, when the bias is high (EB $= 100$), a higher standard deviation can even result in slightly better performance of the supply chain. This result indicates that a positive bias can be used in the forecast as a buffer to protect against uncertainty and thus reduce the negative impact of that uncertainty. The positive bias is more effective in reducing the supplier's total cost than the retailers' cost. The result also shows that the pattern of increase in the standard deviation does not significantly influence the performance of the supply chain.

6.2. *Main effect of information sharing (IS) on supply chain performance*

The Duncan's ranking result in table 5 shows that the effect of information sharing differs significantly for the supplier and the retailers. While the sharing of order information (OIS) always produces lower total costs for the retailers than demand information sharing (DIS), and DIS, in turn, also produces lower costs for the supplier than no information sharing (NIS), the reverse is true for the retailers. This result indicates that information sharing only benefits the supplier but not the retailers. In terms of the total cost of the entire supply chain, OIS results in a better-cost performance than DIS, which performs better than NIS. Since the supplier will make better use of its capacity and improve its on time delivery of goods when retailers share information, information sharing helps the supplier to significantly reduce backorder cost. Furthermore, the supplier will be able to reduce the chances to pay for the transportation of late orders. However, when the supplier delivers more goods to retailers on time, retailers will carry more inventories and thus increase the inventory carrying cost. This effect dominates the decrease in the backorder cost as a result of the on-time delivery performance by the supplier, and thus the total cost for retailers increases when information is shared with the supplier.

From the information in table 5, we can also examine the magnitudes of cost savings or increases for the supplier, the retailers, and the entire supply chain, as a result of information sharing. The cost savings realised through OIS are 69.9 and 9.4% for the supplier and the entire supply chain respectively. DIS provides cost savings of 41.7 and 6.5% for the supplier and the entire supply chain respectively. These figures clearly indicate that significant benefits can be realized through information sharing for the supplier and the entire supply chain. However, this benefit comes at an expense: the cost for retailers increases by 13.8 and 6.0% under order information sharing (OIS) and demand information sharing (DIS) respectively. Therefore, the supplier needs to pass some of its cost savings to the retailers to encourage them to share information.

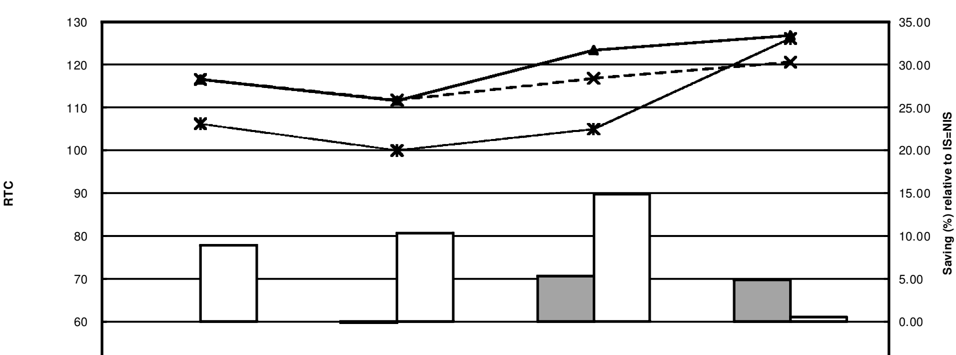
6.3. *Impact of forecasting error distributions (EB and ED) on the value of information sharing (IS)*

Table 4 shows that at the 5% significance level, the two-way interaction of IS with the expected bias (EB) and standard deviation (ED), and its three-way interaction with both EB and ED, are significant for all three dependent variables. To understand how the accuracy of a forecast influences the value of IS, we examine the impact of forecasting errors on IS in the following sections.

6.3.1. *Interaction effect between IS and EB*

To examine the impact of EB on IS, we plotted the relative total cost (RTC) of the supply chain and the cost savings as a result of information sharing under different combinations of IS and EB in figure 5. From the relative total cost figures shown in the chart, we can see that the cost saving of OIS relative to NIS (100*(NIS–OIS)/NIS) first increases as EB is increased from -50 to $+50$. As EB is increased further from 50 to 100, the relative cost saving starts to decrease. The cost saving of DIS relative to NIS (100*(NIS – DIS)/NIS) follows a similar pattern of changes, with the exception that there are no significant savings when EB $= -50$ and 0. Therefore, we can conclude that EB does significantly influence the value of sharing information, and that a moderate level of positive bias can actually increase the cost savings achieved through sharing information.

From figure 5 we can also see that when no information is shared (NIS), or only demand information is shared (DIS), the total cost across different levels of expected bias (EB) does not change much, thus showing that EB has a very significant effect on total cost under these conditions. When order information is shared (OIS), information sharing has much more significant effects on total cost. Under all three levels of information sharing, the total cost first decreases as EB is increased from -50 to 0, and then increases as EB is further increased from 0 to 50 and then to 100. These observations indicate that EB has a greater impact on supply chain performance when retailers share planned order information with the supplier, as the bias in the forecast will be passed to the supplier, which will change its production decisions. These changes will influence total cost for the supply chain.

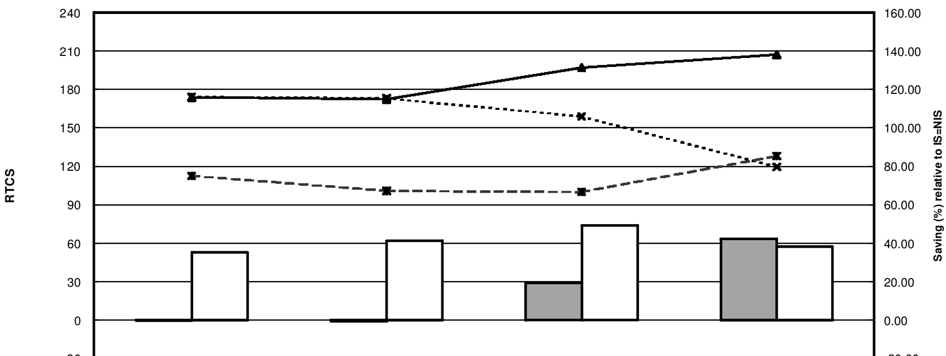


	-50	0	50	100
DIS	-0.01	-0.12	5.35	4.87
OIS	8.92	10.38	14.94	0.53
NIS	117	112	123	127
DIS	117	112	117	121
OIS	106	100	105	126

EB

Figure 5. Relative total cost (RTC) versus expected bias (EB) and information sharing (IS).

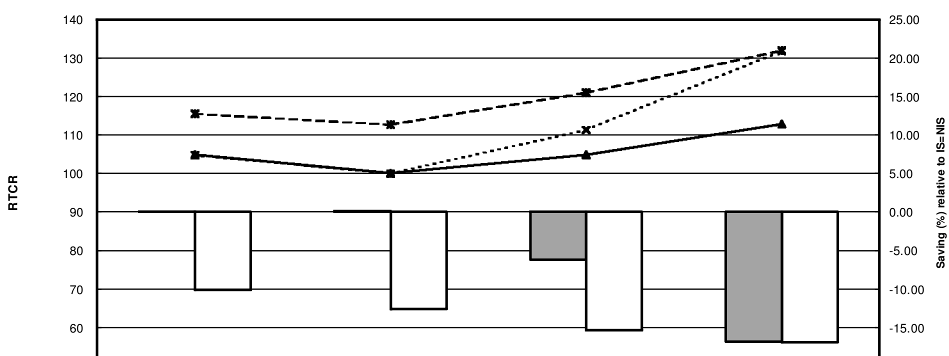
The plots of relative total supplier cost (RTCS) and relative retailers cost (RTCR) versus EB and IS in Figures 6 and 7 show quite different patterns of changes. For the supplier, the cost saving of OIS increases as EB increases from -50 to $+50$ and then it decreases as EB increases from 50 to 100. However, the cost saving of DIS always increases as EB increases from -50 to $+100$. The costs savings for the supplier range between 35.23 and 49.24% as a result of order information sharing. The cost savings of DIS range between -0.45 and 42.28%. For retailers, the total cost first decreases as EB increases from -50 to 0, and then increases as EB



	-50	0	50	100
DIS	-0.14	-0.45	19.27	42.28
OIS	35.23	41.44	49.24	38.17
NIS	174	172	197	207
DIS	174	173	159	120
OIS	113	101	100	128

EB

Figure 6. Relative total supplier cost (RTCS) versus expected bias (EB) and information sharing (IS).



	-50	0	50	100
DIS	0.06	0.09	-6.17	-16.82
OIS	-10.12	-12.58	-15.36	-16.91
NIS	105	100	105	113
DIS	105	100	111	132
OIS	115	113	121	132

EB

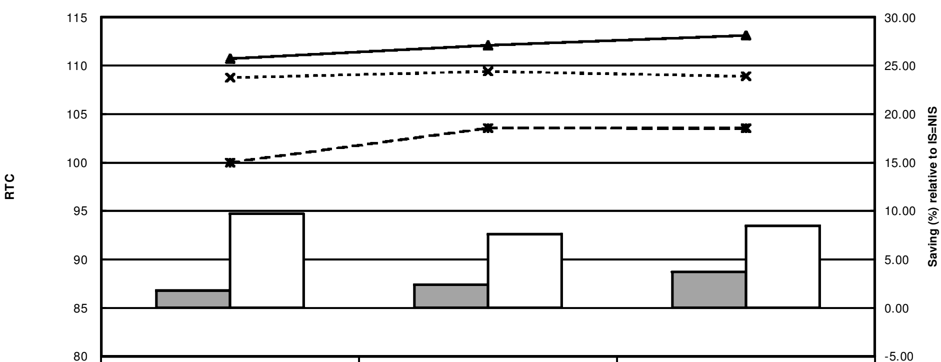
Figure 7. Relative total retailer cost (RTCR) versus expected bias (EB) and information sharing (IS).

increases further from 0 to 50 and to 100 regardless of information sharing. When retailers share future planned orders (OIS) with the supplier, their total costs increase substantially relative to no information sharing. The cost increases become more pronounced as the EB becomes higher. While sharing demand information with the supplier also increases retailers total costs when the EB = 50 and 100, it does not significantly change their costs when the EB = −50 or 0. These results clearly indicate that sharing information will significantly benefit the supplier while it does not benefit the retailers at all under most conditions. As a result, the supplier has to pass some of the cost savings to the retailers in order to motivate them to share information.

6.3.2. *Interaction effect between information sharing (IS) and standard deviation (ED)*

To examine the impact of ED on IS, we plotted the relative total cost (RTC) of the supply chain, and the cost savings, as a result of information sharing under different combinations of IS and ED in figure 8. Figure 8 shows that significant cost savings can be achieved by sharing order information (OIS) under all three levels of the initial standard deviation of the forecast error. The cost savings as a result of demand information sharing (DIS) are lower, but are significant at all levels of ED. Although the increase in ED increases the cost slightly, it does not decrease the value of information sharing. Instead, it increases the value of information sharing in many cases.

Examination of the results for RTCS and RTCR (not shown here) show that while both OIS and DIS will produce significant cost savings for the supplier, they also produce significant cost increases for the retailers. When order information is shared, the supplier can achieve cost savings ranging from 39.62 to 43.51%, while the retailer costs increase by between 13.41 and



	0	50	200
DIS	1.78	2.40	3.72
OIS	9.69	7.62	8.46
NIS	111	112	113
DIS	109	109	109
OIS	100	104	104

ED

Figure 8. Relative total cost (RTC) versus standard deviation (ED) and information sharing (IS).

14.18%. When the demand information is shared, the cost savings for the supplier range from 15.27 to 18.36%, but retailer costs will increase by 5.73 to 6.38%. These results show that either OIS or DIS will reduce the total cost for the supplier while increasing the total cost for retailers. However, the cost savings for the supplier exceed the cost increase for the retailers under both OIS and DIS, and information sharing reduces the total cost of the supply chain. OIS results in more significant improvements in the total cost of the supply chain than DIS. The results also clearly indicate that the supplier has to provide some incentives to the retailers in order for them to share information that will enable performance improvements in the supply chain.

The above results indicate that forecasting error distribution significantly influences the value of information sharing, and therefore supports hypothesis 2. However, only the expected bias (EB) has a major impact on the value of information sharing. The increase rate (IR) and the initial standard deviation (ED) of the forecast error do not seem to significantly influence the value of information sharing. Furthermore, increases in forecasting error may not necessarily reduce the value of information sharing.

6.4. *Effect of interaction between demand pattern (DP), forecasting error distributions (EB, ED and IR) and information sharing (IS)*

The ANOVA results in table 4 show that the DP, the two-way interaction DP*EB and the three-way interaction DP*EB*IS have very significant effects on all three dependent variables. However, the two-way interactions between DP and the other two forecasting error parameters (ED and IR), and the three-way interactions between DP, IS and ED or IR are not significant for all three dependent variables. The following sections discuss how DP influences the performance of the supply chain, IS, and the relationship between IS and EB.

6.4.1. *Impact of DP on supply chain performance*

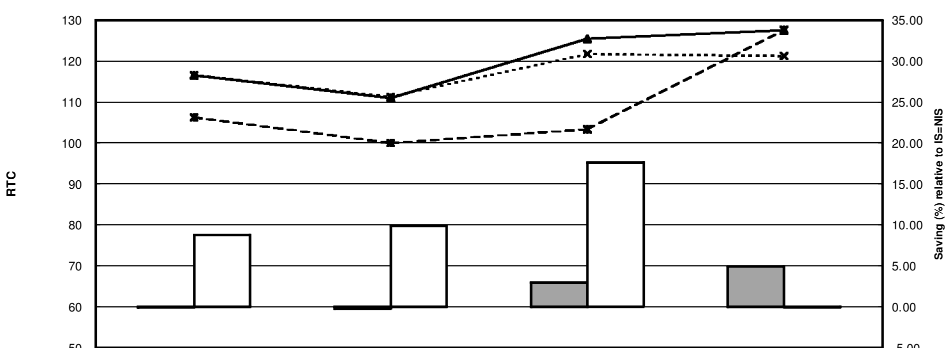
The main effect of DP is shown in table 5. When DP = SDT (demand with seasonality and decreasing trend), the total cost for the supplier, retailers and the entire supply chain are the lowest among the three demand patterns. Demand with seasonality but no trend (SEA) results in the next lowest cost, while demand with an increasing trend and seasonality (SIT) produces the highest total cost for all parties. When DP = SDT, demand is higher during the earlier periods of the simulation horizon. Therefore, the initial inventory will be used up earlier and thus the inventory carrying cost will be lower. As time goes by demand decreases, which leaves more excess capacity. The excess capacity can be used in the later periods to satisfy the backorders. Therefore, the total backorder costs when DP = SDT should also be lower than when DP = SEA or SIT. This is why the total costs are lower for the retailers, suppliers and the entire supply chain. When there is no trend or there is an increasing trend, there will be excess capacity during the earlier periods of the simulation horizon, and these capacities are wasted. At the same time, initial inventories are not used up quickly. When demand outstrips capacity in some later periods, backorders will occur. Therefore, both backorder and inventory carrying costs will be higher. This is why total costs are higher when DP = SEA or SIT.

6.4.2. *Effects of three-way interaction between demand pattern (DP), expected bias (EB) and information sharing (IS)*

To examine the effects of the interaction between DP, EB and IS, we plotted the relative total cost (RTC) of the supply chain under different combinations of EB and IS for DP = SEA, SDT, and SIT in figures 9–11 respectively. Figure 9 shows that when DP = SEA, the lowest total cost is achieved when EB = 0 under all three levels of IS. When EB was increased from 0 to 50, the total costs under NIS and DIS both increased substantially while the total cost under OIS increased only slightly. This means that the cost savings of OIS relative to NIS significantly increased. As EB increased further, the total cost under OIS increased faster and became higher than those under NIS and DIS. Therefore, sharing order information slightly worsens the performance of the supply chain when EB = 100.

The above result indicates that the value of information sharing is significantly influenced by EB. It seems that the sharing of order information produces the highest level of cost savings when EB = 50. When EB increased further, order information sharing actually resulted in performance that was worse than when no information had been shared. This is because sharing information will help to reduce backorder cost and increase inventory-holding costs. When the bias is higher, there is already sufficient buffer stock in the system, and thus the backorder costs are already very low. Therefore, the sharing of information will not significantly reduce the backorder costs, but it will increase the inventory holding cost substantially.

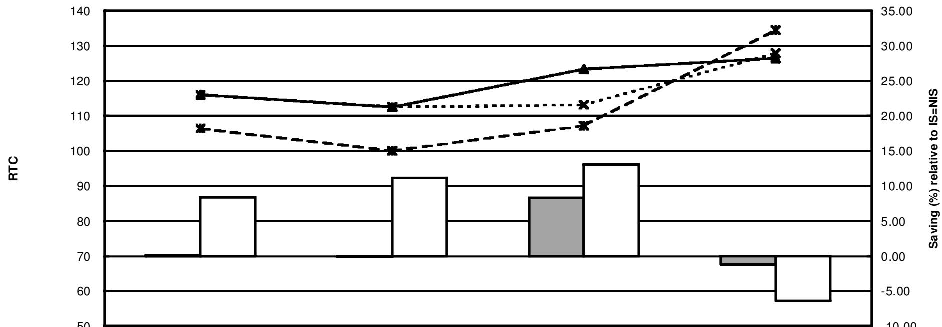
Figure 10 shows that when DP = SIT, the cost savings achieved by the sharing of order information will first increase as EB increases from -50 to 0 and then to 50. When EB increases from 50 to 100, the value of order information sharing (OIS) decreases to a negative figure. When demand information is shared, the cost saving is almost zero when EB = -50 and 0. However, the savings become significant (8.28%) when EB = 50, and then become negative when EB = 100. This pattern of change in



	-50	0	50	100
DIS	-0.08	-0.27	2.96	4.93
OIS	8.80	9.89	17.63	-0.04
NIS	117	111	125	128
DIS	117	111	122	121
OIS	106	100	103	128

EB

Figure 9. Relative total cost (RTC) versus expected bias (EB) and information sharing (IS) (DP = SEA).



	-50	0	50	100
DIS	0.04	-0.08	8.28	-1.16
OIS	8.37	11.11	13.07	-6.35
NIS	116	112	123	126
DIS	116	113	113	128
OIS	106	100	107	134

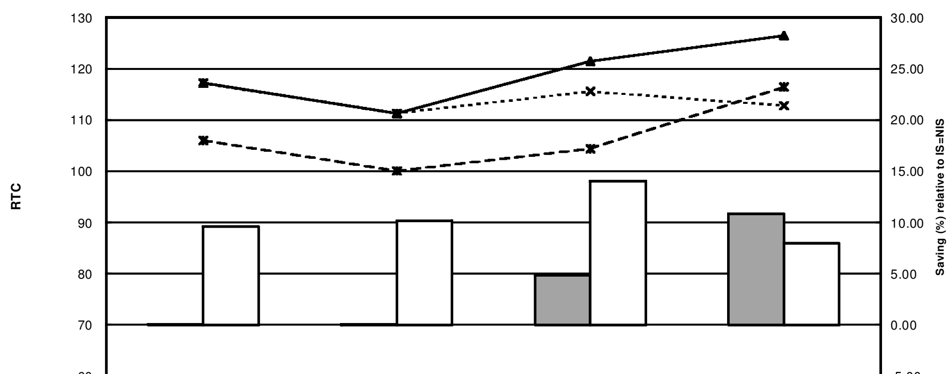
EB

Figure 10. Relative total cost (RTC) versus expected bias (EB) and information sharing (IS) (DP = SIT).

the value of IS is similar to that seen under the SEA demand, except that the value of sharing information shows a greater decline when EB is increased from 50 to 100.

Figure 11 shows total cost under different levels of IS and EB for SDT demand. Again, the pattern of change in IS is similar to that under DP = SIT (figure 10). The major difference is that both DIS and OIS result in significant cost savings at EB = 100 under SDT, while the cost savings are negative under SIT.

The higher value of information sharing under the SDT demand when EB = 100 can be explained by the interaction between the expected bias in the forecasting error and the imbalance between the capacity and forecasted demand. When the demand



	-50	0	50	100
DIS	0.02	-0.02	4.84	10.81
OIS	9.56	10.14	14.05	7.94
NIS	117	111	121	126
DIS	117	111	116	113
OIS	106	100	104	116

EB

Figure 11. Relative total cost (RTC) versus expected bias (EB) and information sharing (IS) (DP = SDT).

has a decreasing trend, the demand is higher in the initial periods of the simulation. When a high positive bias is introduced by the retailers and shared with the supplier through divulging information on planned orders, the supplier cannot produce enough to meet orders placed by the retailers. Therefore, the shared information does not result in earlier or larger orders, and thus the retailers' inventory holding costs are not much increased. When the demand pattern has an increasing trend, however, the forecasted demands are lower than the available capacity during the earlier periods of the simulation horizon, and thus the large positive bias will lead to substantially increased inventory carrying costs when information is shared. This is why information sharing can produce worse performance when the bias is high. The above explanations were supported by detailed examinations of the various component costs for the supplier and retailers.

Such detailed examinations also indicate that the sharing of information provides significant benefits for the supplier and for the entire supply chain under most conditions. However, sharing information hurts the retailers most of the time. While sharing planned order information (OIS) will save the supplier from 34.59 to 51.39% of total cost, it increases the retailers' total cost by 9.59 to 18.59% under the experimental settings of this study. The expected bias in the forecasts and the demand pattern also significantly influence savings or cost increases of sharing information. Under most conditions, positive bias in the retailer's forecasts will make information sharing more beneficial to the supplier while making the retailer's situation even worse. These findings clearly indicate that the supplier has to provide incentives to the retailers in order for them to share information.

Overall, the results in figures 9–11 support the third hypothesis. The demand pattern faced by retailers significantly influences the impact of forecasting error bias (EB) on the value of information sharing. When the demand has an increasing trend, a high positive bias will significantly reduce the value of sharing information. When the demand has a decreasing trend, this effect is less pronounced. Under all three demand patterns, the value of information sharing is highest when there is a slight positive bias (EB = 50).

7. Conclusions

The paper has investigated the impact of forecasting errors on the performance of a supply chain, and the cost savings that can be achieved through sharing information between retailers and the supplier in a supply chain. Through comprehensive simulation experiments and subsequent analysis of the simulation outputs, we have attained the following important findings.

- Both the expected bias and the initial standard deviation of the forecast error significantly influence total costs for the supplier, retailers and the entire supply chain. The rate of increase in the standard deviation of the forecasting errors did not show a significant impact on the supply chain. Furthermore, the interaction between the expected bias and the initial standard deviation is also significant in influencing the performance of the supply chain. When there is a higher variability in the forecasting error, a positive bias in the forecast can help to reduce costs. Therefore, a positive bias in the forecast can be used to protect against uncertainty in the demand forecast.
- Information sharing can significantly influence the performance of a supply chain. When retailers share either the projected net requirement or future

planned order information with a supplier, the supplier can achieve dramatic cost savings. Substantial cost savings can also be achieved for the entire supply chain. However, the retailers usually do not receive any savings. Instead, their total costs are often increased by the sharing of information with the supplier. Furthermore, while sharing of planned order information will produce more significant cost savings for the supplier and the entire supply chain than the sharing of projected net requirement information, it also hurts the retailers more under most conditions. Therefore, this study clearly indicates that suppliers must provide incentives to their retailers for them to make supply chain improvements through information sharing.

- The expected bias of forecasting errors can significantly influence the value of information sharing. The standard deviation and the pattern of deterioration, however, do not significantly influence the value of information sharing. The sharing of information usually results in more cost savings for the supplier and the entire supply chain when there is a slight positive bias in the forecast than when there is no bias or a negative bias. However, the positive bias in the forecast usually also makes information sharing less desirable for the retailers.
- The demand pattern significantly affects how forecasting errors influence the value of information sharing. When there is a strong positive bias in the forecast, the sharing of planned order information can increase the total cost for the supply chain if retailers face demand with an increasing trend. However, when retailers face demand with a decreasing trend, the sharing of information can achieve significant cost savings even when there is a strong positive bias in the forecast. When the expected bias in the forecast is small or zero, the impact of the demand pattern on the value of information sharing is smaller.

These findings enhance our understanding of the benefits of information sharing in a supply chain. The magnitude of possible cost savings or increases for different parties as a result of information sharing can help motivate companies to share information and weigh the cost of sharing information against the benefits. The magnitudes of the cost savings or increases as a result of information sharing can also be used to design incentive schemes to induce information sharing between the supplier and retailers. The results of this study can also help companies to improve the performance of their supply chain by introducing an appropriate level of bias in their forecasts.

Although the findings from this simulation study provide important insights into the possible benefits of information sharing between a supplier and retailers in a supply chain under demand uncertainty, this study also has some limitations. The following are those limitations, and the possible directions of future research:

- The structure of the supply chain used in this study is a simplified case with four retailers and one capacitated supplier dedicated to a single product. There are many possible supply chain configurations. It will be useful to investigate the impact of supply chain structure on the conclusions of this study by varying the ratios between the number of suppliers and retailers. It will also be useful to examine a supply chain with suppliers, manufacturers and retailers.
- We only examined three kinds of information sharing between a supplier and retailers in this study. Other types of information (e.g. inventory levels, capacity, planned production, etc.) can also be shared. Future research should

propose and evaluate these other modes of information sharing. Furthermore, the timing of information sharing is also something that is worthy of further investigation.

- The cost structure (ordering or set-up costs, transportation costs, inventory costs and backorder costs) applied in this study represents one special case. Examination of the impact of cost structures on the effect of information sharing in a supply chain may shed further light on the value of information sharing.
- In this study, we assume that the supplier has a constant capacity and uses a capacitated lot-sizing rule to make its production decisions. It is also assumed that the retailers use EOQ to make their inventory decisions. Investigation of the impact of alternative production and inventory policies on the value of information sharing under different capacity constraints will also be a fruitful area of future research. Alternative policies of capacity adjustment should also be examined.

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