

## **Demand Variability, Forecasting Accuracy, and Supply Information Sharing**

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### **ABSTRACT**

Decision-making needs information. Enterprises in a supply chain make daily operating decisions on the basis of available information of demand and supply. The behaviors of supply chain members would be different under information sharing than otherwise. Demand-side information sharing has been intensively explored. However, supply-side information sharing has not been extensively investigated. This paper examined the impact of supply-side information sharing in a three-stage capacitated supply chain simulation model. In addition, it scrutinized how demand variability and forecasting accuracy moderate the value of supply information sharing. This paper contributes to extending the content and scope of supply chain information sharing research. The findings provide important reference for supply chain managers to implement supply information sharing in order to improve decision-making process, reduce uncertainties, and increase visibility in supply chain operations.

**Keywords:** Supply chain; Supply Information sharing; Simulation

## INTRODUCTION

Individual business competition gives its way to supply chain competition. To be successful in supply chain competition, it is essential that supply chain members coordinate their supply chain operations. Chopra and Meindl (2001) indicated that inventory, transportation, facilities and information determine supply chain performance. Information is potentially the most important element in a supply chain as it glues the other three elements together. However, information should not be fragmented and confined within the four walls of an enterprise; it needs to be shared with other supply chain partners. Needless to say, information sharing is a prerequisite for coordinated supply chain management.

Along a supply chain, information flows from downstream (demand-side) to upstream (supply-side), and from upstream to downstream. Naturally, information sharing can be demand-side information sharing and supply-side information sharing. Demand-side information sharing has been intensively explored, such as, inventory information sharing (Dong & Xu, 2002; Gavirneni, 2006), forecasting information sharing (Cachon & Lariviere, 2001), and order information sharing (Lau, Huang, & Mak et al., 2004; Zhu, Gavirneni, & Kapuscinski, 2010). On the other hand, supply-side information sharing has not been extensively investigated. Therefore, it is worth exploring the effects of supply-side information sharing on the supply chain performance. In addition, a number of operating factors may moderate the effects of supply-side information sharing. Among them, market demand variability and the accuracy of market demand forecasting deserve to be paid more attention because these two factors may significantly interact with supply capability of a supply chain.

This paper is to scrutinize the impact of supply-side information sharing on supply chain performance and the moderating effects of demand variability and forecasting accuracy. A simulation model with mixed-integer programming was built to simulate ordering, production planning, and supplying activities with and without supply information sharing in a three-level capacitated supply chain consisting of three suppliers, one manufacturer and four retailers.

The rest of this paper is structured as follows. Section 2 reviews related literature. Section 3 presents research methodology. Then, in section 4, the research results were discussed. Lastly, section 5 concludes with a summary of major research findings.

## LITERATURE REVIEW

Supply chain concept comes from two-stage inventory models (Beamon, 1998). The early supply chain information sharing studies are based on two-stage structure. Aviv (2001) used single supplier and single retailer structure (dyadic structure). Kim, Leung, Park, Zhang, and Lee (2002) employed multiple suppliers and one supplier structure (convergent structure). Gavirneni (2001) and Zhao and Xie (2002) applied one supplier and multiple retailers structure (divergent structure).

By using the simplest dyadic supply chain structure in their seminal paper, Lee, So, and Tang (2000) developed an analytical model to analyze the benefit of order information sharing. The results revealed that information sharing could provide significant inventory reduction and cost savings to the supplier. The retailer obtains no direct benefits from information sharing alone, but gets benefits from lead time reduction. Aviv (2001) explored forecasting information sharing issue. Further, Cachon and Lariviere (2001) demonstrated the benefit of forecast information sharing in a single product two-level supply chain. Dong and Xu (2002) explored inventory information sharing and showed that even though VMI is proved to have the ability to reduce total inventory-related cost, the supplier may not benefit from this cost reduction, while the buyer takes the biggest share of the cost savings. Gavirneni (2006) indicated that inventory information sharing improved supply chain performance when the supplier offers fluctuating prices. Zhu, Gavirneni, and Kapuscinski (2010) proved that sharing order information from market with the supplier enhanced supply chain performance by 11%.

Other studies analyzed the benefit of information sharing under divergent structure. Gavirneni (2001) modeled a divergent supply chain facing independent and identically distributed (i.i.d.) market demand and found that the benefit of demand information sharing varied with different operating factors, such as supplier capacity, number of retailers, penalty cost, and consumer demand variance. Zhao and Xie (2002) designed a simulation model with divergent structure to investigate the impact of demand information sharing and forecast errors on supply chain performance and clearly indicated that significant benefits can be realized through information sharing for all parties in the supply chain, especially for the supplier. This finding is similar to Ballou, Gilbert, and Mukherjee (2000), Lee et al. (2000), and Yu, Yan, and Cheng (2001).

The supply chain information sharing research under two-stage structure gives numerous insights into the value of information sharing in terms of cost saving and inventory reduction. However, Chen, Drezner, Ryan, and Simchi-Levi (2000) thought that these studies clearly do not capture many complex characteristics involved in supply chains in the real world. To be more realistic, Huang and Gangopadhyay (2004) conducted a simulation study to examine the efficacy of demand information sharing under a four-level divergent supply chain structure. The results showed that upstream members gain more from information sharing than downstream members do. Wu and Cheng (2008) analytically investigated the value of demand information sharing in a three-level serial supply chain and found that the upstream supply chain members, such as the distributor and the manufacturer, experience inventory and expected cost reduction because of increased information sharing. The fact that the benefit of demand-related information sharing was largely obtained by upstream supply chain members may discourage downstream members from sharing information. Therefore, Ding, Guo, and Liu (2011) designed a benefit allocation mechanism in a three-level divergent supply chain to motivate retailers to share demand information.

More recently, Arshinder, Kanda, and Deshmukh (2011) indicated that the existing literature addresses the information sharing issues in divergent and convergent multi-level structures insufficiently. Similarly, Jeong and Leon (2012) pointed out that a more complex convergent or divergent supply chain structure should be used in the future research. Therefore, it is necessary to construct supply chain structures that are complex enough to be representatives of reality and simple enough to be dealt with for research. It

seems that three-level supply chain combining divergent and convergent structure is a good balance between the closeness to reality and research complexity.

As we know, a supply chain faces uncertain market demands from one side and unstable supply capability from another side. In order to better align demand with supply, a supply chain member, such as a manufacturer, not only needs to know demand-side information from its downstream partners, but also has to consider supply-side information from its upstream partners. So far, demand-side information sharing has driven the studies on information sharing (Choi, 2010). What information could be shared from supply-side has been paid less attention. Chopra and Meindl (2001) indicated that supply capability of products and production capacity could be the supply information needed by downstream supply chain members. Swaminathan, Sadeh, and Smith (1997) analytically investigated the influence of sharing supplier capacity information with a downstream manufacturer on a simple two-tier supply chain structure for a single product in a single period horizon. Kim et al. (2002) developed a two-level convergent supply chain model to determine how much of each raw material is to be ordered from each supplier under the constraints of capacities of suppliers as well as the manufacturer. Xue, Shen, Tan, Zhang, and Fan (2011) measured the impacts of supply quantity information on a two-level supply chain in construction industry.

The existing literature shows that information sharing research relies heavily on analytical approach. Most real supply chains are too complex to be evaluated analytically (Law and Kelton, 2000). Arshinder et al. (2011) claimed that analytical approach may not be able to tackle the dynamic interactions of a supply chain. Because close-form solutions cannot easily be derived from analytical models, many analytical information sharing research often have to resort to simulations to prove optimality (Choi, 2010). Huang and Gangopadhyay (2004) indicated that simulation approach is a useful and powerful tool in studying supply chain behaviors. Simulation models can be closer to real systems than analytical models. Therefore, simulation approach may be a right choice for modeling complex supply chain structures.

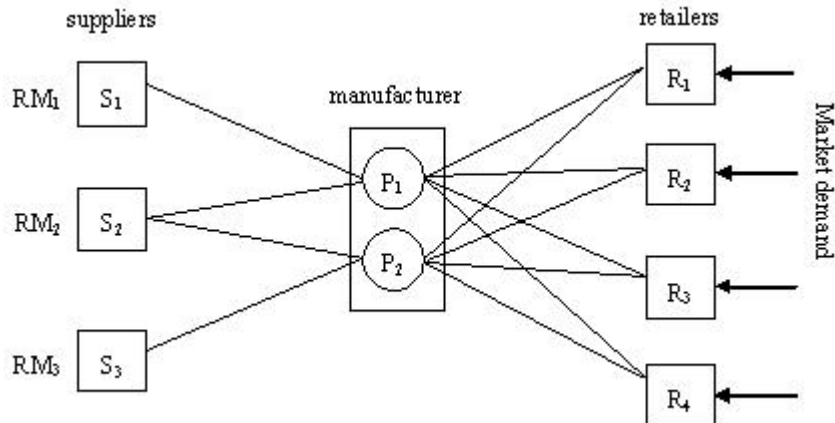
## RESEARCH METHODOLOGY

This paper uses a hybrid approach of computer simulation and mixed-integer programming (MIP). A computer program is built to simulate the operations of a three-stage manufacturing supply chain by using C++ and runs on a Dell PowerEdge 4400 server with Linux operating system.

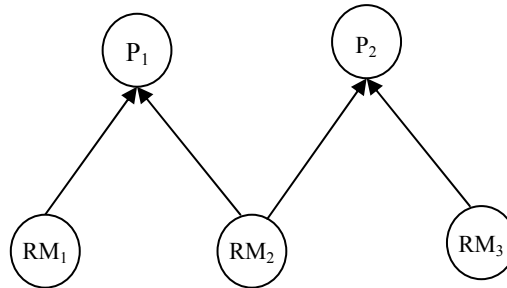
### Basic Assumptions

We make the following assumptions to simplify the supply chain model:

- 1) The supply chain consists of three capacitated suppliers, one capacitated manufacturer, and four retailers (Figure 1).

**Figure 1: Supply Chain Structure**

- 2) The manufacturer produces two functional products in a make-to-stock process, which consume the same key resource and can substitute each other to some extent. Production lead time is assumed to be zero. Capacity absorption rate for both products is equal to one, that is, one unit of product needs one unit of resource to produce.
- 3) Each product needs two raw materials, and one of the two raw materials is a common one (Figure 2). The usage rate of all the raw materials for the two products is one.

**Figure 2: The Products Structure**

- 4) The retailers face uncertain and time-varying customer demands for both products. The average demand for each product is 1000 units at each period. In turn, the manufacturer faces demands from the retailers for replenishing their inventories, so the retailers' average demand for each product is 4000 units at each period. Sufficient initial inventories are provided for each retailer and the

- manufacturer to avoid not having enough inventories to satisfy demands at the beginning of the simulation. The manufacturer places orders for raw materials to its suppliers when inventories of raw materials are not enough.
- 5) The lead times of placing orders from the retailers to the manufacturer and from the manufacturer to raw material suppliers are zero.
  - 6) The suppliers are end suppliers; thus they do not need to order raw materials from other suppliers to make their own products.
  - 7) The manufacturer employs MRP system to organize its production.
  - 8) Each supplier is the only provider for the manufacturer for one specific raw material, and the manufacturer is the only customer for each supplier.
  - 9) Transportation lead time from the suppliers to the manufacturer and from the manufacturer to the retailers is one period. Transportation capacity of a vehicle is large enough for any large order.
  - 10) Downstream partners pay for the regular transportation cost, and upstream partners pay for backorder transportation cost.
  - 11) The cost structure: all cost figures are from a real case of a local soft drink manufacturer whose supply chain structure is similar to the one we studied.

## Independent Variables

The independent variables used in the simulation model are summarized in Table 1 and described as follows.

**Table 1: Independent Variables**

Variables	Label	Levels	Values
Supply-side Information Sharing	SSIS	2	NIS, SIS
Demand Pattern	DP	3	SEA, SIT, SDT
Forecasting Error Bias	EB	4	-50,0,50,100
Forecasting Error Deviation	ED	3	0,50,200

**Supply-side information sharing (SSIS).** Available-to-promise (ATP), an important and advanced concept in master production scheduling (MPS) process, is well-suited to be a supply-side information indicator. According to Blackstone (2010, p.9), ATP is “the uncommitted portion of a company’s inventory and planned production, maintained in the master production schedule to support customer order promising.” It checks whether a customer’s order can be satisfied and provides customers with accurate information about their suppliers’ product availability at certain periods of time. Two levels of SSIS, no supply information sharing (NIS) and supply information sharing (SIS), will be examined. NIS means upstream members do not share supply information with downstream members. SIS means upstream members share supply information with downstream members.

**Demand pattern (DP).** Three demand patterns representing different combinations of trends and seasonality will be examined. SEA produces demand with seasonality without trend. SIT generates demand with seasonality and increasing trend.

SDT generates demand with seasonality and decreasing trend. These demand patterns are generated for four retailers by the following formula.

$$\text{Demand}_{it} = \text{Base} + \text{Slope} \bullet t + \text{Season} \bullet \sin\left(\frac{2\pi}{\text{SeasonCycle}} \bullet t\right) + \text{Noise} \bullet \text{snormal}_i() \quad (1)$$

where  $\text{Demand}_{it}$  is the demand at period  $t$  for retailer  $i$  ( $i=1,2,3,4$ ;  $t=0,1,2,\dots, 409$ ); Base is the initial demand which is selected to ensure that the average demand for each product during all simulation period is 1000; Slope describes the increasing or decreasing trend of demand; Season represents the magnitude of seasonal variation of demand; SeasonCycle is the cycle of the seasonal variation of demand, and its value is seven representing a weekly fluctuation; Noise is the magnitude of random disturbance;  $\text{snormal}_i()$  is a standard random function. To avoid the possibility of generating negative demand, we restricted the standard normal random variable to values within the range of  $-3.0$  to  $+3.0$  only.

This demand formula has been extensively used in a series of MRP simulation studies (Zhao, Lai, & Lee, 2001) and supply chain simulation studies (Zhao & Xie, 2002; Abuhilal, Rabadi, & Sousa-Poza, 2006; Schmidt, 2009), which appropriately captures the characteristics of demand variability. The characteristics of three demand patterns for two products are summarized in Table 2.

**Table 2: The Characteristics of Demand Patterns**

Demand Patterns	Product 1				Product 2			
	Base	Slope	Season	Noise	Base	Slope	Season	Noise
SEA	1000	0	200	100	1000	0	200	200
SIT	761	1	200	100	551	2	200	200
SDT	1239	-1	200	100	1449	-2	200	200

**Forecasting error distribution.** Following the approach used by Biggs and Campion (1982), Bhaskaran (1998), and Zhao and Xie (2002), the forecast made by the manufacturer is equal to the demand plus the forecasting errors, which is assumed to follow normal distribution. Three parameters, forecasting error bias (EB), forecasting error deviation (ED) and forecasting deviation increasing rate (IR), portray the forecasting error distribution, which, in turn, describe forecast accuracy. Thus, the demand forecast made at period  $t_0$  for period  $t$  ( $t \geq t_0$ ) is generated by the following formula:

$$\text{Forecast}_{it} = \text{Demand}_{it} + \text{EB} + \text{ED} \bullet \text{IR} \bullet (t - t_0 + 1) \bullet \text{snormal}_i() \quad (2)$$

Where  $\text{Demand}_{it}$  and  $\text{snormal}_i()$  have the same meaning as in formula (1). The values of EB are set at  $-50$ ,  $0$ ,  $50$ ,  $100$ ; the values of ED are set at  $0$ ,  $50$ , and  $200$ ; and the value of IR was set as linear, that is, a constant increasing rate.

## Dependent Variables

Supply chain cost and service levels have been used as the dependent variables of the simulation model to measure the supply chain performance:

**Total cost of retailers (TCR).** It is the sum of ordering cost (including transportation cost), inventory carrying cost and the backorder cost for the retailers.

**Total cost of suppliers (TCS).** It is the sum of the transportations cost (for backorder delivery), inventory carrying cost and the backorder cost for the suppliers.

**Total cost of manufacturer (TCM).** It is the sum of the setup cost, order processing cost, transportations cost (for backorder delivery), inventory carrying and the backorder cost for the manufacturer.

**Total cost of the supply chain (TC).** It is the sum of TCR, TCS and TCM, minus backorder cost paid by the manufacturer to the retailers and by the suppliers to the manufacturer. We subtract backorder costs because they are only internal costs within the supply chain.

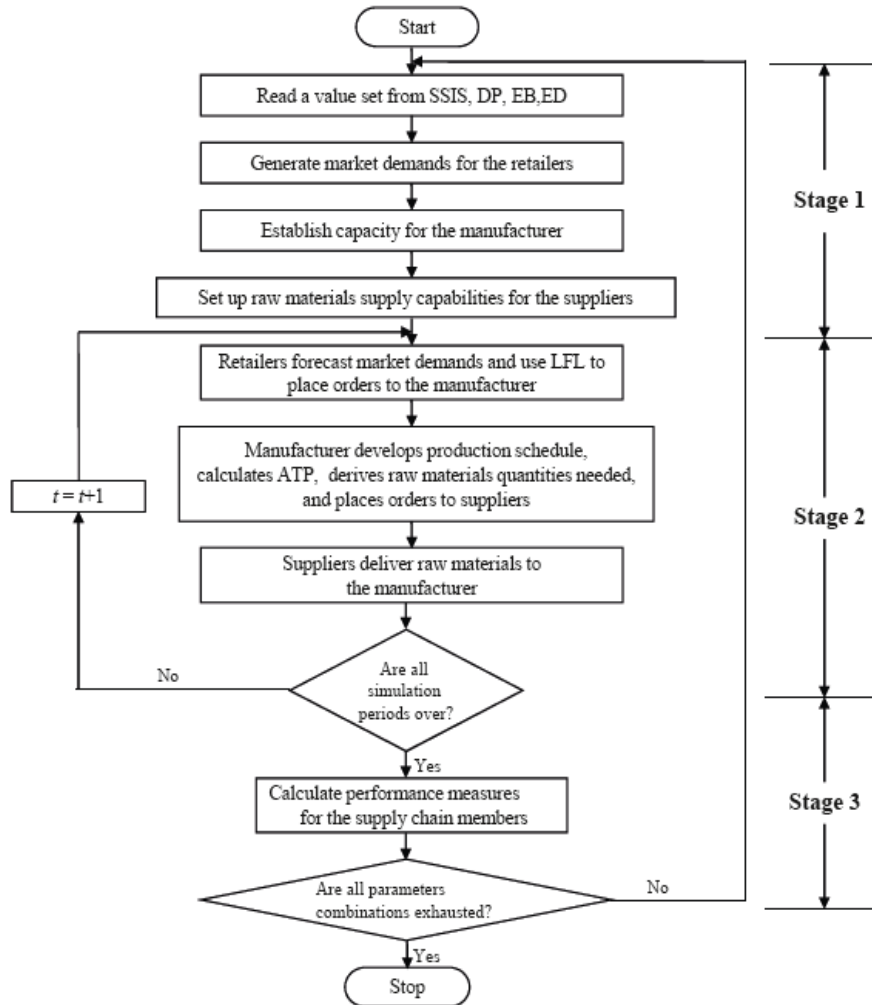
**The service level of the supply chain (SL).** It is the percentage of customer demand satisfied by the entire supply chain. SL is also the actual service level performance of the retailers because only the retailers have external customers. Therefore, the service level of the retailers represents how well the supply chain serves its customers.

## The Simulation Procedure

The simulation program developed by Zhao, Xie, and Leung (2002) and Zhao and Xie (2002) was used to simulate forecasting, ordering, and supplying activities in the supply chain. Genetic algorithm for general capacitated lot-sizing problem (GCLSP) developed by Xie and Dong (2002) was modified to solve MIP model for the manufacturer to develop production schedule. An interface was built to link these two parts so that simulation parameters could be transferred interactively between them. The simulation flow chart is presented in Figure 3.

The simulation runs last for 410 periods. The first 50 periods are warm-up periods during which the data generated are not used to analyze simulation results. The last 10 periods are also excluded from the calculation of the performance measures to eliminate the effect of transportation lead times. Therefore, the data in 350 periods are analyzed and used for performance calculation (from period 50 to period 399). These cut-off values were determined empirically in order to reach a steady state during simulation (Zhao et al., 2002).



**Figure 3: Simulation Flow Chart**

## Research Hypotheses

Three hypotheses will be tested in this study:

**Hypothesis 1:** The supply information sharing (SIS) will significantly improve supply chain performance.

**Hypothesis 2:** Forecasting error distribution (EB, ED) will have significant influence on the value of supply information sharing.

**Hypothesis 3:** Demand patterns faced by the retailers (DP) will significantly influence the impact of forecasting error distribution (EB, ED) on the value of supply information sharing.

## RESULTS AND DISCUSSIONS

For each combination of the independent variables, 20 replications were conducted to reduce random effects. Thus, total simulation runs are  $2*3*4*3*20=1440$ . The outputs from the simulation experiments were analyzed by using Analysis of Variance (ANOVA). The results are presented in Table 3 and Table 4. We can see that all the main effects and the interaction effects are statistically significant in terms of total cost and service level at 1 percent significance level. The discussions, which centered on the research hypotheses, are presented as follows.

**Table 3: ANOVA Results for Cost Performance**

Dependent Variables		TC	
Source		F Value	Pr>F
1	SSIS	4756.45	<.0001
2	EB	133.11	<.0001
3	ED	712.34	<.0001
4	DP	538.97	<.0001
5	SSIS*EB	350.60	<.0001
6	SSIS*ED	335.92	<.0001
7	EB*ED	204.58	<.0001
8	SSIS*DP	321.78	<.0001
9	SSIS*EB*ED	997.60	<.0001
10	SSIS*EB*DP	399.77	<.0001
11	SSIS*ED*DP	285.85	<.0001

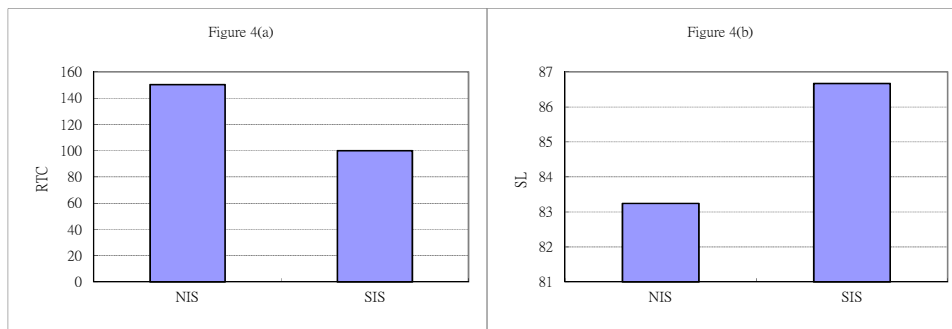
**Table 4: ANOVA Results for Service Level Performance**

Dependent Variables		SL	
Source		F Value	Pr>F
1	SSIS	7048.02	<.0001
2	EB	233.63	<.0001
3	ED	1462.91	<.0001
4	DP	313.83	<.0001
5	SSIS*EB	137.00	<.0001
6	SSIS*ED	458.72	<.0001
7	EB*ED	143.60	<.0001
8	SSIS*DP	298.56	<.0001
9	SSIS*EB*ED	205.41	<.0001
10	SSIS*EB*DP	390.19	<.0001
11	SSIS*ED*DP	229.57	<.0001

## The Impact of Supply Information Sharing (SIS) on the Supply Chain Performance

Figure 4(a) and Figure 4(b) show the main effects of supply information sharing (SIS) on the total cost and service level of the supply chain, respectively. The total cost numbers are relative with the minimum being 100. When supply information is shared, the total cost of the whole supply chain is greatly reduced. The total cost saving is more than 50 percent. Service level of the whole supply chain under supply information sharing is slightly higher than that of no supply information sharing (approximately 3.4 percent). It seems that supply information sharing has more powerful effect on total cost reduction than on service level improvement. Based on these observations, hypothesis 1 is supported.

**Figure 4: Main Effect of SIS on Relative Total Cost (RTC) and Service Level (SL)**

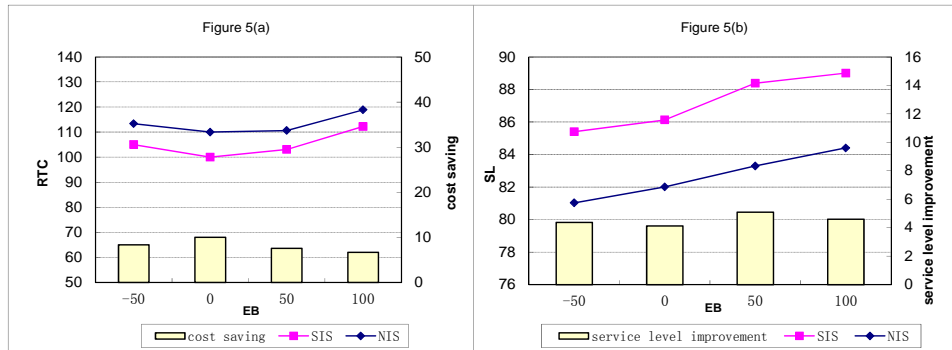


The significant cost reduction from supply information sharing could be explained as follows. By knowing supply information from its suppliers, the manufacturer can develop a feasible production schedule that satisfies its internal constraints and external constraints, simultaneously. On the other hand, through sharing supply information with the retailers, the manufacturer can reduce backorders cost and transportation cost by selling substitute products to the retailers. Meanwhile, knowing supply information from the manufacturer, the retailers are able to adjust their purchasing plans by moving the procurement quantities backward or by buying substitute products, thus reducing backorders and increasing sales.

## The Impact of EB on the Value of SIS

To analyze the impact of EB on the value of supply information sharing, we portrayed the relative total cost (RTC) and service level (SL) of the supply chain for different combinations of EB and SSIS in Figure 5.

**Figure 5: Interaction between EB and SSIS on Relative Total Cost (RTC) and Service Level (SL)**



As shown in Figure 5(a), the cost saving of SIS relative to NIS is decreased as EB varied from 0 to 100. RTC achieved the lowest when EB=0 under both NIS and SIS due to a more accurate forecast. In addition, the cost saving when EB=0 is the largest. When EB becomes positive or negative, the cost savings are all decreased. Therefore, EB significantly influences the value of SIS in terms of cost saving.

The service level under NIS increased with a constant rate when EB changed from -50 to 100, as shown in Figure 5(b). The service level under SIS increased first with a flat rate when EB changed from -50 to 0, with a steeper rate when EB changed from 0 to 50, then it increased slowly again when EB changed from 50 to 100. Therefore, the EB significantly influences the value of SIS in terms of the service level, and a positive EB can improve the service level through sharing supply information. This is because a positive EB causes production to be consistently higher than the actual demand, thus introducing appropriate protection function of safety stock.

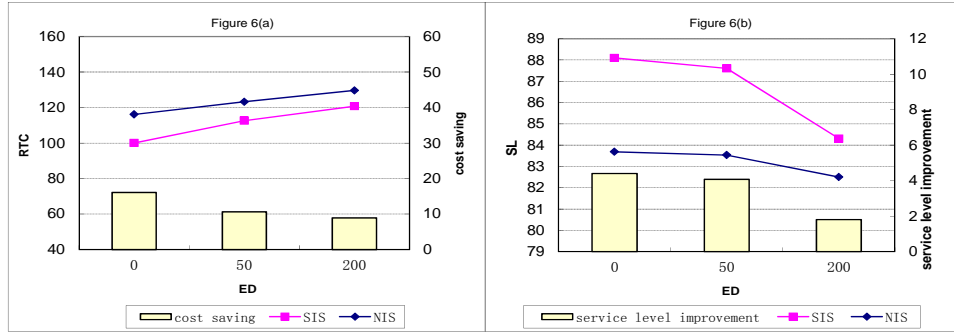
### The Impact of ED on the Value of SIS

Figure 6 illustrates RTC and SL of the supply chain for different combinations of ED and SSIS.

As shown in Figure 6(a), the cost saving reached the largest when ED=0, then the cost saving when ED=50 is slightly higher than that when ED=200. Basically, ED decreased the value of supply information sharing. Hence, it is cost-effective to share supply information when ED is small. This implies that ED significantly influences the value of supply information sharing in the form of cost saving.

Figure 6(b) shows that the service level improvement also decreased with the increase of ED. However, moderate ED does not hurt too much. Only high ED greatly lowers service level improvement. The finding indicates that ED has a significant impact on the value of supply information sharing in terms of service level improvement. Based on these observations, hypothesis 2 is supported.

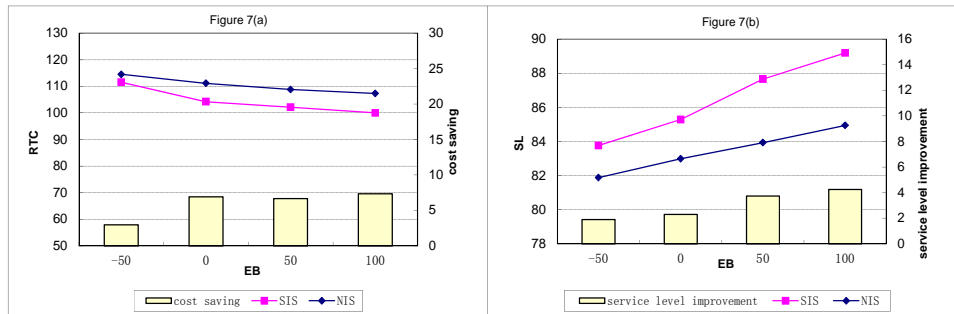
**Figure 6: Interaction between ED and SSIS on Relative Total Cost (RTC) and Service Level (SL)**



**The Influence of DP on the Impact of EB on the Value of SIS**

Figure 7, Figure 8 and Figure 9 illustrate RTC and SL of the supply chain for different combinations of DP, EB and SSIS.

**Figure 7: Interaction between EB and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SDT**

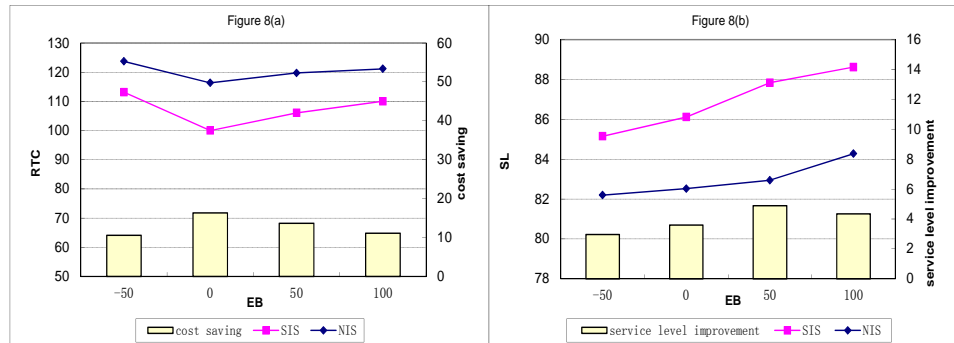


As shown in Figure 7(a), RTC decreased steadily under both NIS and SIS when EB changes from negative to positive. The cost saving under EB=-50 is far lower than those under positive EB. When DP=SDT, demands at earlier periods are higher than supply capacity at the same periods, and gradually becomes lower than supply capacity at later periods. Backorders mainly appear at the earlier periods. Because of the negative bias, the manufacturer will produce less than what retailers need over each planning horizon. Hence, the negative bias actually increases total supply shortage to retailers, thus increasing the backorder cost of the whole supply chain. Under such situation, supply

information sharing cannot help retailers in making better purchasing decisions to reduce backorders. When EB turns to be positive, there will be overproduction at later periods. This overproduction can satisfy those backorders at earlier periods. In addition, supply information enables retailers to make better purchasing plans to prepare against backorders. Therefore, the cost savings under positive bias are larger than those under negative bias.

Because a larger forecast error bias actually improves the service level of the whole supply chain due to the effect of safety stock, as shown in Figure 7(b), the service level goes up consistently when EB changes from -50 to 100 under both NIS and SIS. The service level increases with a steeper slope when there is supply information sharing than when there is no supply information sharing.

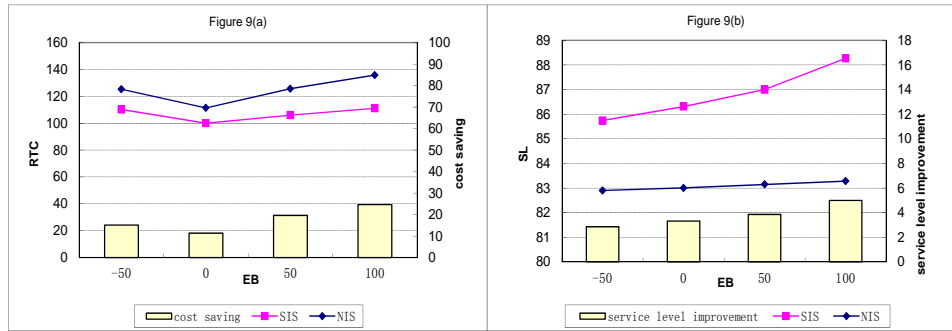
**Figure 8: Interaction between EB and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SEA**



When DP has only seasonal variation, as depicted in Figure 8(a) and Figure 8(b), the impact of EB shows a different pattern from the one when demand pattern has a decreasing trend. The cost saving is increased when EB increased from -50 to 0, and then decreased when EB further increased to 50 and 100. Therefore, when EB=0, cost saving is the largest. In addition, as shown in Figure 8(b), the service level improvement is increased when EB increased from -50 to 50 and then dropped a little when EB reached 100. In general, supply information sharing is more beneficial under positive EB than under negative EB.

When DP=SEA, demand variation would be relatively smooth during each planning horizon. Capacity deficiency would not occur only at earlier or later periods, but across all planning horizons. Under such situation, supply information can be more helpful for retailers to alter their purchasing plan to avoid backorders. Although holding cost will be reduced in the presence of negative EB, backorder cost will definitely increase. When EB turns to be positive, on one hand, overproduction at the manufacturer may cut backorder cost at the expense of increased inventory holding cost; on the other hand, an inflated demand may surpass capacity if the positive bias is too large. Only when EB is zero can total cost be the lowest and cost saving be the largest.

**Figure 9: Interaction between EB and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SIT**



As shown in Figure 9(a), the cost saving reached the highest when EB=100. Figure 9(b) shows that SL increased in an increasing rate under SIS but only increased slightly under NIS when EB increased from -50 to 100.

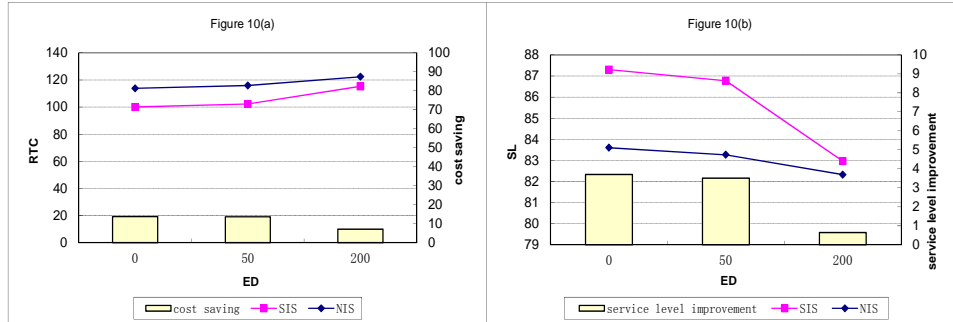
When DP=SIT, demands at earlier periods are lower than supply capacity at the same periods, and gradually becomes higher than supply capacity at later periods. So backorders would mainly appear at the later periods. Utilizing supply information, retailers can move part of their orders to earlier periods to avoid backorders. However, increased inventory holding cost will stop them from doing this without limit.

The negative EB makes the manufacturer produce less than what is actually needed, thus generating more backorders at later periods. Even if supply information is shared, retailers cannot use it to make an appropriate purchasing plan to avoid backorders. When EB becomes positive, the manufacturer produces more than what is actually needed at earlier periods. Backorders at later periods will decrease because the manufacturer can use excess production at earlier periods to satisfy demands at later periods. On the other hand, knowing supply information, retailers can move their purchasing orders at later periods to earlier periods. Therefore, positive EB results in larger cost savings and higher service level improvement.

### The Influence of DP on the Impact of ED on the Value of SIS

Figure 10, Figure 11 and Figure 12 illustrates RTC and SL of the supply chain for different combinations of DP, ED and SSIS.

**Figure 10: Interaction between ED and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SDT**



As shown in Figure 10(a), under SIS, RTC slightly increased as ED increased from 0 to 50, and then increased more rapidly to 200. Under NIS, RTC increased in a flat rate as ED increased from 0 to 50, and then to 200. As shown in Figure 10(b), under SIS, the service level first decreased slightly as ED increased from 0 to 50, and then decreased abruptly as ED further increased to 200. Under NIS, the service level decreased in a flat rate as ED increased from 0 to 50, and then dropped sharply as ED further increased to 200.

When DP=SDT, high demand variability aggravated the situation of capacity deficiency at earlier periods even further and made the manufacturer's production planning more difficult. Therefore, the backorders at earlier periods are more likely to rise. On the other hand, the quality of supply information deteriorates. Therefore, only when ED is zero or moderate does supply information play a relatively large role in improving supply chain performance.

**Figure 11: Interaction between ED and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SEA**

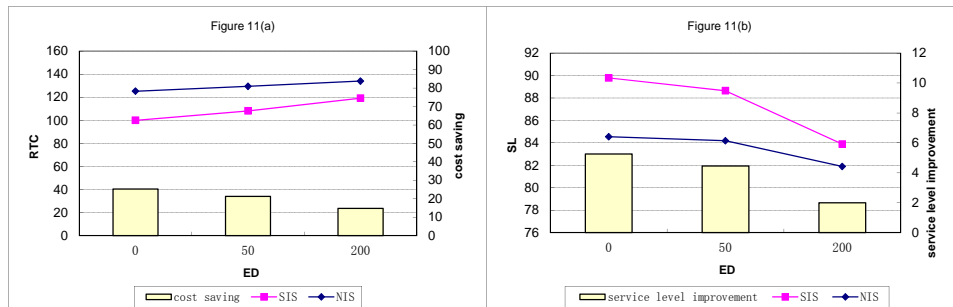
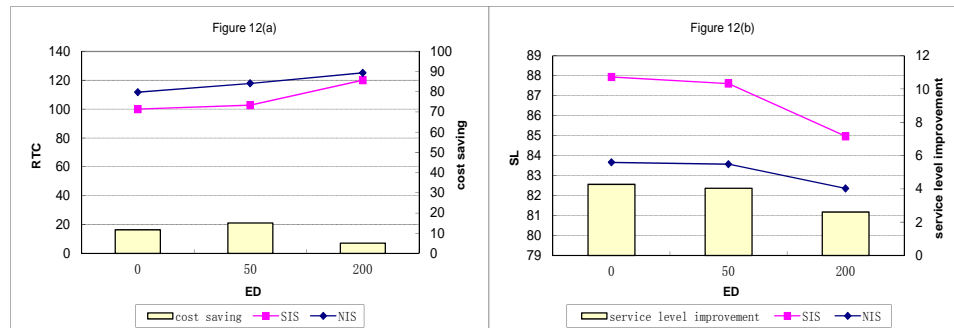




Figure 11(a) illustrates the cost saving is the highest when  $ED=0$  and decreases with the increase of  $ED$ . Figure 11(b) shows that under SIS, the service level first decreased slightly as  $ED$  increased from 0 to 50, and then decreased greatly as  $ED$  further increased to 200. Under NIS, the service level also followed the same variation pattern as under SIS when  $ED$  increased from 0 to 50.

When the demand pattern has only seasonal variation, demand would be relatively smooth. When  $ED$  is large, the orders received by the manufacturer will be more volatile than the demands retailers faced. The larger  $ED$  is, the less smooth the order pattern will be, the more order surge will occur, and the more likely that backorders will appear at some periods. On the other hand, when supply information is shared, retailers can revise their purchasing decision to reduce backorders as much as possible so that both total cost and service level can be improved. However, the larger  $ED$  is, the lower the value of supply information sharing is likely to be.

**Figure 12: Interaction between ED and SSIS on Relative Total Cost (RTC) and Service Level (SL) when DP=SIT**



As shown in Figure 12(a), the cost saving reached the lowest when  $ED=200$  and the highest when  $ED=50$ . Figure 12(b) displays that under SIS, the service level first decreased slightly as  $ED$  increased from 0 to 50, and then decreased abruptly as  $ED$  further increased to 200. Under NIS, the service level decreased in a flat rate as  $ED$  increased from 0 to 50, and then dropped sharply as  $ED$  further increased to 200.

When the demand pattern has an increasing trend and  $ED$  grows larger, more volatile orders may make supply deficiency at later periods even worse. If supply information is shared, retailers know exactly when there are enough products. Because backorders appear primarily at later periods, retailers may move their original orders at later periods to earlier periods. Thus, inventory holding cost will increase in exchange for decreased backorder cost and improved service level. Relatively speaking, under SIT, retailers have more room to utilize supply information to adjust their purchasing plan than under SDT. Therefore, the service level improvement under SIT is larger than that under SDT when  $ED$  is large. Based on the discussions in the previous two subsections, hypothesis 3 is supported.

## CONCLUSIONS

This paper has investigated the impact of supply-side information sharing on supply chain performance and the moderating effects of demand variability and forecasting accuracy. Analyses of the simulation results reveal the following important findings.

Supply information sharing significantly reduces the total cost and enhances the service level of the whole supply chain. Forecasting accuracy, characterized by forecasting error bias and forecasting error deviation, has significant influence on the value of supply information sharing. A larger forecast error bias simultaneously results in a higher service level and higher total cost. A positive forecast error bias causes larger service level improvement, while a zero forecast error bias contributes to the largest cost saving. A higher forecast error deviation always results in worse supply chain performance, lower service level improvement, and smaller cost saving.

The impact of forecast accuracy on the value of supply information sharing is heavily moderated by demand variability which expressed as different demand patterns that retailers face. Positive forecast error bias always leads to the better service level improvement across different demand patterns. Positive forecast error bias also brings the largest cost saving when demand has increasing or decreasing trend. Zero forecast error bias results in the largest cost saving only under demand without trend. In addition, a higher forecast error deviation reduces the value of supply information sharing in terms of both cost saving and service level improvement under all demand patterns but in different degrees. Supply information sharing achieves the better performance improvement when demand shows seasonal variation only.

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