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The Impact of Forecast Errors on Early Order Commitment in a Supply Chain*

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ABSTRACT

Supply chain partnership involves mutual commitments among participating firms. One example is early order commitment, wherein a retailer commits to purchase a fixed-order quantity and delivery time from a supplier before the real need takes place. This paper explores the value of practicing early order commitment in the supply chain. We investigate the complex interactions between early order commitment and forecast errors by simulating a supply chain with one capacitated supplier and multiple retailers under demand uncertainty. We found that practicing early order commitment can generate significant savings in the supply chain, but the benefits are only valid within a range of order commitment periods. Different components of forecast errors have different cost implications to the supplier and the retailers. The presence of trend in the demand increases the total supply chain cost, but makes early order commitment more appealing. The more retailers sharing the same supplier, the more valuable for the supply chain to practice early order commitment. Except in cases where little capacity cushion is available, our findings are relatively consistent in the environments where cost structure, number of retailers, capacity utilization, and capacity policy are varied.

Subject Areas: Forecasting, Material Management, Simulation, and Supply Chain Management.

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INTRODUCTION

In recent years, many industries have shifted their foci of continuous improvements from internal operation efficiency to the overall efficiency of trade relationships. Various industries have embarked on industry-wide initiatives that promote information sharing and integration across the stakeholders in the supply chain. Initiatives such as Quick Response of the U.S. apparel and textile industries and Efficient Consumer Response of the grocery industry have yielded dramatic improvements in the speed, efficiency, and accuracy by which goods can be manufactured, distributed, and sold to the consumers (Kurt Salmon Association, 1993). The premise of these initiatives is that increased efficiencies could be gained through co-managed business processes and shared information.

Although these recent initiatives help reduce forecast errors, a company's forecasting capability remains an important asset because unreliable forecasts result in inefficiencies in the supply chain. Moreover, supply chain partnership involves mutual commitments. One form of such commitments is early order commitment. An early order commitment is a firm purchase order, fixed in both quantity and delivery time, made by a retailer to the supplier earlier than a planned lead time for manufacturing and delivery. For example, Wal-Mart and Warner-Lambert used Listerine, a popular brand of oral cleaning liquid, to test the collaborative forecasting concept and software. Wal-Mart agreed to extend its order cycle from nine days to six weeks to match the manufacturing time for Listerine and share the risks (Koloszyc, 1998).

When retailers make an order commitment early, the supplier has ample time to prepare for the production and better utilize his resources, thus reducing production and logistic costs. On the contrary, orders of short notice and last-minute order changes are likely to cause inefficiency and extra costs in the supply chain. The supplier may bear such costs in the short run, but in the long run these costs tend to be affected by every stakeholder in the supply chain. When product demand exceeds supply, early order commitment helps a customer to secure a portion of the supplier's capacity or a promise of on-time delivery. However, to a retailer, committing an order early faces a risk of over- or underforecasting the demand. The risk can be high when demand uncertainty is high or when the quality of demand forecast is questionable. Therefore, it would be critical to quantify and compare these cost implications to determine if sufficient savings to the entire supply chain can be generated to justify the efforts of practicing early order commitment. Moreover, how "early" should the order be committed and what factors may have significant impacts on such a decision are questions of interest in this paper.

In this research we explore the benefits of practicing early order commitment in the supply chain. We investigate the complex interactions between early order commitment and forecast errors by simulating a supply chain with a capacitated supplier who supplies to multiple retailers. We study the impact of forecast error on the value of early order commitment. Three components of forecast error are analyzed, including forecast bias, forecast deviation, and the increased rate of forecast deviation with time. Specifically, we address the following four research questions:

1. Which component of forecast error has the greatest impact on the total system cost in a supply chain?

2. Does early order commitment help reduce the total system cost in a supply chain? If so, what are the benefits to the supplier and to the retailers, respectively? How does forecast error affect the selection of early order commitment periods?
3. Holding forecast errors at the same level, how do trends and seasonality in demand affect the decision of early order commitment?
4. How robust are the findings that address the above three research questions under different operational settings, such as cost structure, number of retailers, capacity utilization, and capacity adjustment policy?

Our results indicate that practicing early order commitment can generate significant system-wide savings in the supply chain, but the benefits are only valid within a "feasible range" of early order commitment periods. To reduce total system cost, controlling forecast deviation is as critical as controlling forecast bias, while the increase rate of forecast deviation is an insignificant factor. Early order commitment is more beneficial to a supply chain when the demand contains trend, especially a negative trend. In addition, the more retailers sharing one supplier, the more valuable it is for the supply chain to practice early order commitment. Except in cases where little capacity cushion is available, these findings are consistent across the operational settings we explored.

This paper is organized as follows. The next section presents the related literature. We then describe the supply chain environment and explain the design of the simulation experiment. The experimental results and insights to the research questions are discussed next, followed by the summary and conclusions.

LITERATURE REVIEW

In prior research that studies the impact of forecast errors on production planning within a manufacturing entity, a common approach is to separately control the forecast bias and forecast deviation (variability). Lee and Adam (1986) and Lee, Adam, and Ebert (1987) reported that while both forecast bias and standard deviation significantly affect MRP system performance, bias had a more significant impact. Ritzman and King (1993) analyzed the impact of forecast errors on total inventory and past due demand in an MRP system with uncertainties in demand, supply, and lead time. They also found that in most circumstances, forecast bias is much more crucial to system performance than is forecast variability. Lin and Krajewski (1992) developed an analytical model to study the impact of frozen interval and replanning interval of master production schedules under uncertain demand. Lin, Krajewski, Leong, and Benton (1994) tested that analytical model and found that the choice of frozen interval has a more significant impact than the choice of the replanning interval. They also showed that the magnitude of the forecast errors play relatively minor roles in the choice of these intervals. Bhaskaran (1998) did a simulation study at General Motors Corp. 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 that forecast deviation accelerates as the forecasts go further into the future: constant rate, decreasing rate, and increasing rate.

Academic research that studies the impact of forecast errors on the supply chain is relatively new. Lee, Padmanabhan, and Whang (1997) analyzed the phenomenon that demand variability amplifies as one moves up a supply chain. Using a first-order autoregressive demand (AR(1)), they mathematically proved that the demand variation was amplified when orders were passed to the supplier. This phenomenon is called the bullwhip effect. They analyzed four causes of the bullwhip effect as demand forecasting processing, rationing game, order batching, and price variations. Improved information sharing and market channel alignment are major remedies among others. Metters (1997) studied the impact of induced demand seasonality and increased forecast error caused by the bullwhip effect. His results indicate that eliminating the induced seasonality alone can increase the overall profitability of the system (i.e., supply chain) by 10-20%, while decreasing the forecast error alone can increase profitability by 5-10%. However, his experiment treated the supply chain as a system and did not distinguish the number of stages in the supply chain, nor the number of retailers or suppliers in each stage. Baganha and Cohen (1998) developed an analytical model to demonstrate that inventories can sometimes have a stabilizing effect on the supply chain and that bullwhip effect is not always present throughout the supply chain.

Chen, Drezner, Ryan, and Simchi-Levi (2000) quantified the bullwhip effect for a simple, two-stage supply chain consisting of a single retailer and a single manufacturer. They assumed that the retailer's demand followed an AR(1) process and used a simple order-up-to inventory policy to make inventory replenishment decisions. They also assumed that the retailer used the simple moving average model to forecast the demand. They demonstrated that the magnitude of the variance was significantly influenced by the number of observations used in the moving average, the lead time between the retailer and the manufacturer, and the correlation parameter in the demand function. In particular, when the number of observations used in the simple moving average is large, the increase in order variability is negligible. However, when that number is small, there can be a significant increase in variability. In other words, the smoother the demand forecasts, the smaller the increase in variability. They also found that the bullwhip effect could be reduced, but not completely eliminated, by sharing retailer demand among all parties in the supply chain.

In another paper, Chen, Ryan, and Simchi-Levi (2000) investigated the impact of simple exponential smoothing forecasts on the bullwhip effect. They found that for i.i.d. demands, or demands with a linear trend, exponential smoothing forecasts lead to a larger increase in order variability than moving average forecasts. A retailer forecasting a demand with a linear trend will have more variable orders than a retailer forecasting a demand without trend. These two papers by Chen et al. evaluated the magnitude of the variance amplifications in the supply chain by considering alternative demand processes and forecasting models. However, they did not consider the impact of the variance amplifications on the cost and service level of the supply chain. Furthermore, their studies were based on a supply chain with a single supplier and a single retailer, and did not consider factors such as inventory cost, ordering cost, production setup cost, and production decisions by the manufacturer.

Gilbert and Ballou (1999) proposed a model to quantify the benefits to the supplier from obtaining advanced commitments from downstream customers. In deriving the model, they assumed that the demand of the supplier followed a Poisson process and the processing times are exponentially distributed. Their model provides some price discount bounds for a supplier to use advanced order commitments as a means of offering lower purchasing prices to his customers. But, their model does not address the costs of the customers nor the impact of forecasting accuracy as the customers place orders in advance.

As Gilbert and Ballou (1999) indicated, little research has addressed the benefits that accrue to a supply chain when downstream firms are given incentives to provide earlier commitment to purchases. They also realized that only by understanding the cost implications of advanced order commitment can a firm offer price incentives benefiting both itself and its customers. In addition, most studies in the supply chain literature made many assumptions to simplify the environment in an attempt to build tractable analytical models. Common assumptions in the literature include no cost for placing an order, the use of an (s, S) inventory control and ordering policy by the retailers, and infinite supply from the supplier with no batching in production. While these analytical models help researchers and practitioners develop insights to the innovative approaches of supply chain integration, they do not necessarily provide enough guidance for practicing managers to implement the proposed approaches. In this study, we develop a simulation model that captures a rich set of cost items and demand patterns in order to explore the benefits of practicing early order commitment for all the members in a supply chain. With a simulation model, we not only can examine the impact of forecast error on a retailer's decision of committing orders earlier, but we also conduct experiments on a variety of environments by changing cost structure, number of retailers, level of capacity utilization, and capacity adjustment policy.

THE SUPPLY CHAIN ENVIRONMENT

Background and Basic Assumptions

We develop the base case experiment to investigate the first three research questions. We then perform various sensitivity analysis experiments to address the fourth research question. To establish a realistic environment for our experiments, we visited a soft drink bottling plant and discussed the parameter designs of the supply chain in the experiments with the company's supply chain manager. In the base case the supply chain consists of one supplier (the bottling plant) and four retailers (supermarkets that sell this soft drink). The cost parameters used in the base case are either real data from the company or estimates that we derived after we consulted the manager. The supplier is a manufacturer with a capacitated facility that produces a single product for the retailers. No explicit manufacturing leadtime will be considered because the conclusions will not change as long as the lead time is fixed. However, the production lead time as a result of insufficient capacity is implicitly determined in the supplier's production decision. Only the retailers face customer demand, and the average demand per period for each retailer is 1,000 cases. The retailers replenish their inventories from the supplier by placing orders to him. Therefore, the average demand per period for the supplier is 4,000 cases. The number of periods that the retailers place orders in advance, called early order commitment, is to be examined in the simulation experiment.

The shipments of products are delivered from the supplier to the retailers by trucks, and the transportation lead time from the supplier to each retailer is one period. The truckload is assumed to be large enough (or equivalently, the product is small enough in size and weight) so that a shipment to each retailer in each period can be completed by a single truck. The estimated transportation cost per truck from the supplier to a retailer is based on the distance. Whenever a retailer places an order to the supplier, a fixed-order processing cost of $30 per order is incurred. Because only one truck is needed for one order delivery, the actual ordering cost for a retailer is the sum of the single truck transportation cost and the fixed-order processing cost. The production setup cost of the supplier is estimated to be around $500 per setup. This includes the opportunity cost for the production setup time and the material cost for setting up the production run. The inventory carrying costs per unit per period (h) for the supplier and the retailers are also estimated based on the soft drink company's accounting records and on the supply chain manager's estimates. These costs include the rental and operation of warehouse space and the opportunity cost of the capital. The annual inventory costs for both the supplier and retailers are estimated to be about 18% of the item value in the base case. Since the cost per case is $30 for the supplier and $40 for the retailers, the daily inventory carrying costs are 0.18*30/365=$0.015/case*day and 0.36*40/365= $0.02/case*day, respectively. We also estimate the unit backorder cost per day. It is estimated to be at 1% of the product value per day for the base case. We use three other combinations of backorder cost and carrying cost in the first sensitivity analysis experiment that will be explained in detail later. Table 1 summarizes these cost structures.

The length of the simulation run is selected in such a way that the termination effect will be minimized (430 periods in this study). The first 50 periods and the last 30 periods are excluded from the performance measures calculations to eliminate the effects of the transportation and ordering lead times. Therefore, the final performance measures are calculated based on 350 simulation periods (from period 50 to period 399). Furthermore, in order to avoid possible backorder for the retailers during the first few periods immediately following the 49th period because of transportation lead time, sufficient initial inventory is assumed for each retailer. In this study, we set the initial inventory in the 49th period for the ith retailer at $(14 + i)*1000$ ($i = 1, 2, 3, 4$). The second part of the initial inventory ($i*1000$ units) is used to make different retailers have different initial inventories. The simulation procedure consists of three phases, to be discussed below.

Phase I: Generation of the Demand and the Capacity

The first phase of the simulation generates demands for all the retailers and the available aggregate capacity for the single resource of the supplier. Demand for each retailer is generated by a corresponding demand generator using the following formula:

Table 1: Cost structures for the supplier and four retailers.

Supplier/Retailer	Supplier	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Case 1 (Base Experiment): Low Inventory Carrying cost and **Low** Backorder Cost					
Order Processing Cost ($/order) (Transportation Cost Excluded)	500 (Setup cost)	30	30	30	30
Transportation Cost ($/truck)	N/A	450	255	331	553
Carrying Cost ($/unit/period)	0.015	0.02	0.02	0.02	0.02
Backorder Cost ($/unit/period)	0.30	0.40	0.40	0.40	0.40
Case 2: Low Inventory Carrying cost and **High** Backorder Cost					
Order Processing Cost ($/order) (Transportation Cost Excluded)	500 (Setup cost)	30	30	30	30
Transportation Cost ($/truck)	N/A	450	255	331	553
Carrying Cost ($/unit/period)	0.015	0.02	0.02	0.02	0.02
Backorder Cost ($/unit/period)	1.50	2.0	2.0	2.0	2.0
Case 3: High Inventory Carrying cost and **Low** Backorder Cost					
Order Processing Cost ($/order) (Transportation Cost Excluded)	500 (Setup cost)	30	30	30	30
Transportation Cost ($/truck)	N/A	450	255	331	553
Carrying Cost ($/unit/period)	0.03	0.04	0.04	0.04	0.04
Backorder Cost ($/unit/period)	0.30	0.40	0.40	0.40	0.40
Case 4: High Inventory Carrying Cost and **High** Backorder Cost					
Order Processing Cost ($/order) (Transportation Cost Excluded)	500 (Setup cost)	30	30	30	30
Transportation Cost ($/truck)	N/A	450	255	331	553
Carrying Cost ($/unit/period)	0.03	0.04	0.04	0.04	0.04
Backorder Cost ($/unit/period)	1.50	2.0	2.0	2.0	2.0

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

where

$Demand_t$ = demand in period t (t = 0, 1, 2, ..., 429),

snormal() = standard normal random number generator, and

SeasonCycle = 7 in this study.

The other parameters (*base*, *slope*, *season*, *noise*) are characteristic parameters for the demand generators, among which *base* is selected to ensure that the average demand for the 350 simulation periods (from the 50th period to 399th period) is 1,000. Because there is a normal variant in the demand generation function, the demand generated may take a negative value. We consider this possibility negligible and will impose the restriction that the standard normal random number generator only produces the random number from –3.0 to +3.0; thus, no negative value will be possible for the demands. The season cycle of seven days is used to represent a weekly variation in sales faced by many retailers. These demand generators given in equation (1) were used in Zhao and Lee (1993).

We assume in this study that all retailers face an identical demand pattern in a given time, although the exact amount of demand varies among the retailers due to randomness. Three demand generators are used: SEA is the pattern with seasonalities but without trends, SIT has seasonalities and a positive trend, while SDT has seasonalities and a negative trend. The demand patterns and their characteristic parameters are listed in Table 2.

In this study, we assume that the capacity requirement for each unit of product equals one, as was the case in almost all the models we reviewed in the literature. That is, one unit of resource is required by the supplier to produce exactly one unit of product. This assumption will not change the generality of the conclusion because the demand for a product can always be measured by the units of the resource needed to produce that product. Once the demands for all retailers are generated for the 430 periods, the total capacity needed to produce all the items can be calculated, for the total capacity needed equals the total demand of all retailers over all the periods. In the base case, the available capacity is assumed to be at a constant level during the entire simulation horizon so that the overall capacity utilization is 80%. In the sensitivity analyses, we test two other levels of capacity utilization at 70% and 90%. We also explore a policy of allowing the capacity to be adjusted from period to period.

Phase II: Retailers' Ordering Decisions

For a retailer the planning horizon of the purchasing plan is 32 periods, which is eight times the natural ordering cycle, and the re-planning periodicity equals one period. Based on demand forecasts, a retailer decides when and how many units to order from the supplier by using the economic order quantity (EOQ) policy. The retailer must place the order to the supplier (OC + 1) periods in advance, where OC is the level of early order commitment and the one period is the transportation lead time. Once the order is placed, it is considered "frozen" and cannot be changed. Since the replanning interval is fixed at one period, in each planning cycle a retailer needs to calculate the net requirements for the remaining (32 – OC) "free" periods. If the EOQ formula indicates that an order for the first free period is needed, this order will be placed (and committed) to the supplier. All the future orders in the rest of the free intervals are not placed and can be updated in the next planning cycle. For example, when OC = 5, the retailer must place an order six periods in advance based on forecasts, whereas the supplier must deliver the product five periods later, and this delivery will arrive at the retailer one additional period later due to the transportation lead time. Then, at the end of the period, the actual customer demand is realized. The retailer fills the customer's order (plus backorder if there is any) by on-hand inventory, and any shortages will become backorders.

Phase III: Supplier's Production and Delivery Decision

The supplier is assumed to be a manufacturer that, in planning its production activities, applies a single-item capacitated lot-sizing rule as developed by Chung and Lin

Table 2: Demand patterns.

Demand Generator	Base	Slope	Season	Noise
SEA	1,000.0	0	200	100
SIT	551.0	2	200	100
SDT	1,449.0	–2	200	100

(1988). This efficient algorithm can find the optimal solution in polynomial time. The supplier receives orders from four different retailers and makes production-planning decisions based on the available information. At the end of each period, and after the current period's production is finished, the supplier makes shipping decisions from on-hand inventory. The supplier fills each retailer's order (plus backorder if there is any) if on-hand inventory is sufficient to fill all retailers' orders and backorders. If on-hand inventory is insufficient, each retailer will be allocated by a quota proportional to its order (plus backorder if there is any), and any shortages will become backorders. The shipment will arrive at the retailers via trucks after the transportation lead time. As we have pointed out above, we assume the truckload is large enough so that a single truck can complete a shipment to any retailer in any period.

The party to whom the transportation cost will be charged depends on whether there is a placed order from the retailer corresponding to the shipment. When the retailer places an order in the current period, the retailer picks up the bill for the transportation cost of the current period's shipment, regardless of whether a proportion of the shipment is used to satisfy the backorder of previous orders. When the retailer does not place an order in the current period, the shipment to the retailer is only used to satisfy the backorders of previous orders. In this case, the supplier picks up the bill for the transportation cost of the current period's shipment.

This process is repeated until ordering, production, and delivery decisions are developed for all 430 periods. After the entire simulation run is completed, all the cost items will be calculated for the retailers and the supplier. The aggregate total cost will also be calculated and used as the performance measure for the supply chain. As pointed out in previous paragraphs, all performance measures are calculated based on the data from the 50th period to the 399th period.

EXPERIMENTAL DESIGN

Experimental Factors for the Base Case

The experimental factors used in the base case include demand pattern (DP), early order commitment periods (OC), and forecasting error distribution parameters. The parameters of the demand patterns are given in Table 2. We selected the following values as the OC periods: (0,5,10,15,20). The forecasting errors are assumed to be normally distributed and are characterized by three parameters: the mean (also called bias) of forecast errors (EB), the initial standard deviation (ED) that measures forecast variability, and the increase rate (IR) of forecast deviation along time. We set EB at (–5%, 0, 5%, and 10%) and ED at (0, 5%, and 20%) for the demand described in equation (1). Adopting the idea from Bhaskaran (1998) that was discussed in the literature review section, we selected three patterns of increase rate (IR) for forecast deviation: linear, concave, and convex. However, in the initial experiments we performed, the results across three patterns of IR were of little difference. Therefore, we dropped IR from the experimental factors, and then used the linear increasing rate (1/4.85) throughout the experiment. Hence, the demand forecast made at period t_0 for a period $t(t \geq t_0)$ is generated according to the following formula:

$$Forecast_t = Demand_t \times \{1 + EB + ED \times [1 + (t - t_0)/4.85] \times snormal()\}, \tag{2}$$

where

$Demand_t$ is the demand in period t (t = 0, 1, 2, ..., 429) as given in equation (1) and *snormal*() is a standard normal random number generator. The experimental factors and their values used in the base case are summarized in Table 3. Because of the way we define EB in equation (2), a positive EB represents overforecasting the demand, while a negative EB stands for underforecasting the demand.

Experimental Factors for Sensitivity Analyses

Realizing that some other factors may influence the results of the base case, we conducted four sensitivity analyses by varying the cost structure (CS), the capacity tightness (CT), the number of retailers (NR), and the capacity changing policy (CP). For the cost structure, we varied the inventory carrying cost and the backorder costs because there are often subjective components in their estimation, especially the backorder cost. As discussed above, we estimated the inventory carrying cost to be 18% per year and the backorder cost to be 1% of the item value per day. These costs can be significantly higher for other companies in the soft drink industry. Therefore, we increased these costs in the sensitivity analyses. In Case 2, we increased the backorder cost to 5% of the item value while keeping the inventory carrying cost the same. In Case 3, we increased the inventory carrying cost to 36% per year while keeping the backorder cost the same as in the base experiment. In Case 4, we increased both the inventory carrying cost and backorder costs. These cost figures are summarized in Table 1.

To examine the impact of the ratio between the number of retailers and suppliers, the number of retailers is varied from one (NR = 1) to eight (NR = 8) in the second sensitivity analysis. The capacity tightness (CT) is varied from a capacity utilization rate of 70% (CT = Low) to that of 90% (CT = High) in the third sensitivity analysis. Thus, CT = Low has the most capacity cushion when needed. Moreover, in the base case experiment, we assume that the capacity remains at a fixed level and cannot be adjusted during the entire simulation horizon (CP = constant). In the fourth sensitivity analysis, we perform simulation experiments with the assumption that the capacity can be adjusted period by period based on the demand (CP = changing).The parameters setting used in the sensitivity analyses are summarized in Table 4.

Table 3: Summary of the experimental factors for the base case.

Variable Number	Variable Name	Label	Number of Levels	Values
1	Retailer's Demand Patterns	DP	3	SEA, SIT, SDT
2	Forecast Bias	EB	4	–5, 0, 5, 10 (%)
3	Forecast Deviation	ED	3	0, 5, 20 (%)
4	Order Commitment Period	OC	5	0, 5, 10, 15, 20 (periods)

Table 4: Parameters varied in the sensitivity analyses.

Sensitivity Analyses	Parameters Varied	Label	Number of Levels	Values
1	Cost Structure*	CS	4	Case1 (Base), Case2, Case3, Case 4
2	Number of Retailers	NR	3	1:1; 1:4 (Base); 1:8
3	Capacity Tightness	CT	3	Low: 70% utilization; Med: 80% utilization (Base); High: 90% utilization
4	Capacity Policy	CP	2	Constant (Base); Changing

*See the detailed cost parameters for these cases in Table 1.

Performance Measures

The following performance measures are used in the experiments:

1. Total cost for retailers (TCR), which is the grand sum of the ordering costs (including transportation costs), inventory carrying costs, and backorder costs among all the retailers.
2. Total cost for the supplier (TCS), which is the sum of the setup cost, transportation cost (for backorder deliveries), inventory carrying cost, and backorder cost for the supplier (BCS).
3. Total cost for the entire supply chain (TC), which is the sum of the TCR and TCS, but deducts the backorder cost paid from the supplier to the retailers (BCS). We subtract BCS from the total cost because it is not a real cost if the retailers do not charge the supplier when they run out of stock.

RESULTS AND ANALYSIS

The Base Case

For each combination of the experimental factors, five replications were conducted in the simulation to reduce the random effects. The output from the base case simulation experiments was analyzed using the SAS analysis of variance (ANOVA) procedure and the Duncan's test. The results are presented in Tables 5 and 6. The residual analyses from SAS suggested that transformations of the performance measures were necessary to meet the assumptions of normality independence, and equal variances of the errors that ANOVA requires. We discuss the data analysis and the results in the sequence of the four research questions that this paper ,addresses.

Table 5: Selected ANOVA results.

Factors	TC(1)			TCS(2)			TCR(3)		
Source	*R*-square	*F*-Value	*Pr > F*	*R*-square	*F*-Value	*Pr > F*	*R*-square	*F*-Value	*Pr > F*
DP	.0337	1094.26	<.0001*	.0261	572.76	<.0001*	.0270	1125.56	<.0001*
EB	.0230	497.38	<.0001*	.0004	6.50	<.0002	.0527	1467.14	<.0001*
ED	.0468	1518.11	<.0001*	.0058	127.30	<.0001*	.0680	2839.56	<.0001*
OC	.7833	12699.90	<.0001*	.9342	10250.30	<.0001*	.6479	13519.90	<.0001*
DP*EB	.0002	2.25	<.0372	.0004	2.80	0.0106	.0004	6.23	<.0001*
DP*ED	.0008	12.40	<.0001*	.0033	35.97	<.0001*	.0001	1.36	.2477
DP*OC	.0682	553.24	<.0001*	.0062	33.79	<.0001*	.1420	1481.57	<.0001*
EB*ED	.0013	14.32	<.0001*	.0001	0.62	.7173	.0036	50.11	<.0001*
EB*OC	.0125	67.71	<.0001*	.0006	2.14	.0128	.0204	141.94	<.0001*
ED*OC	.0160	129.33	<.0001*	.0016	8.81	<.0001*	.0262	273.54	<.0001*
DP*EB*ED	.0002	1.28	.2238	.0003	0.97	.4778	.0001	0.99	.4604
DP*EB*OC	.0010	2.73	<.0001*	.0012	2.13	.0014	.0007	2.55	<.0001*
DP*ED*OC	.0002	0.74	.7519	.0021	5.79	<.0001*	.0004	1.98	.0121
EB*ED*OC	.0009	2.34	.0003	.0003	0.55	.9620	.0012	4.31	<.0001*

(1) Based on residual analysis and suggestion by SAS, inverse square-root transformations of TC (i.e. 1/sqrt(TC)) was made to satisfy the assumptions of ANOVA.
(2) Based on residual analysis and suggestion by SAS, logarithm transformations of TCS (i.e., $\log_{10}$(TCS)) was made to satisfy the assumptions of ANOVA.
(3) Based on residual analysis and suggestion by SAS, square-root transformations of TCR (i.e., sqrt(TCR)) was made to satisfy the assumptions of ANOVA.
*Significant at .0001 level
Labels: DP-demand pattern, EB-forecast bias, ED-forecast deviation, OC-early order commitment period, TC-total supply chain cost, TCS-total cost for the supplier, TCR-total cost for the retailers.

Table 6: Duncan's grouping on main effects.

Dependent Variables		TC	TCS	TCR
Source		RANK	RANK	RANK
DP	SEA	1	1	2
	SIT	2	2~3	1
	SDT	3	2~3	3
EB	–5	2	1	2
	0	1	2~4	1
	5	3	2~4	3
	10	4	2~4	4
ED	0	1	1~2	1
	5	2	1~2	2
	20	3	3	3
OC	0	5	5	1
	5	1	4	2
	10	2	3	3
	15	3	1	4
	20	4	2	5

*The Duncan's groupings were performed at the .05 significant level based on the transformed values as described in the footnote of Table 4.

**Labels: DP = demand pattern, EB = forecast bias, ED = forecast deviation, OC = early order commitment period, TC = total supply chain cost, TCS = total cost for the supplier, TCR = total cost for the retailers.

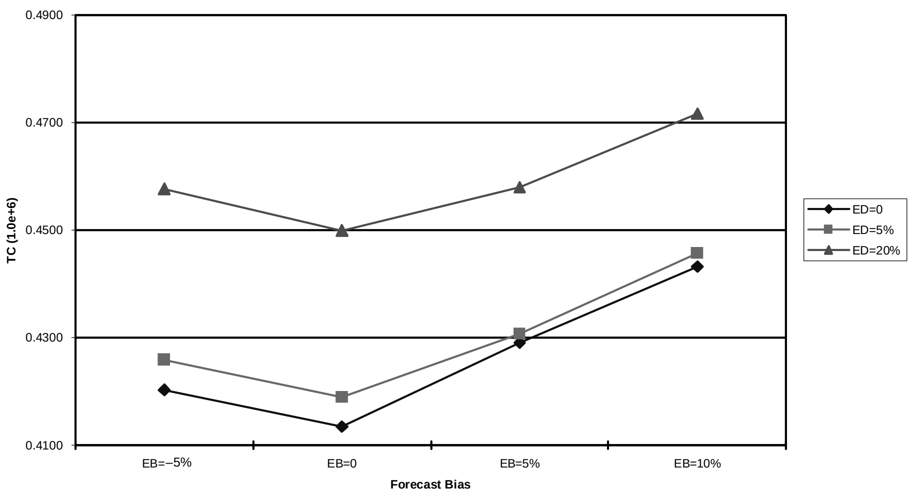
Impact of the components of forecast error

The first research question examines which component of forecast error has the greatest impact on TC. In an earlier section, we stated that the pattern of increasing rate for forecast deviation was not a significant factor and had been dropped from further analysis. The ANOVA in Table 5 shows that both forecast bias (EB) and forecast deviation (ED) are significant in all three cost measures. However, ED has larger F-values than EB. This may be attributed to a large maximum value of ED (20%) used in the experiment.

Figure 1 provides the plot of TC curves on various combinations of ED and EB. Figure 1 shows that TC is the lowest when ED = 0 and EB = 0. The more these forecast error components deviate from zero, the higher the TC. The Duncan's groupings in Table 6 show that TCR, TCS, and TC all increase as ED increases from 0 to 20%. The impact of ED on the TCS is relatively smaller than that on the TCR and TC. These results indicate that a higher variability in the demand forecast (ED) does increase the costs of the supplier, the retailers and, hence, the entire supply chain. However, the detrimental effect of EB is not as straightforward. Among the four levels of EB, EB = 0 has the lowest TC and TCR, but not TCS.

As for TCR, negative and positive forecast biases (EB) have different implications. The plot of TCR curves shows a similar pattern as seen in Figure 1 and,

Figure 1: Interaction of forecast bias (EB) and forecast deviation (ED) on total supply chain cost (TC).



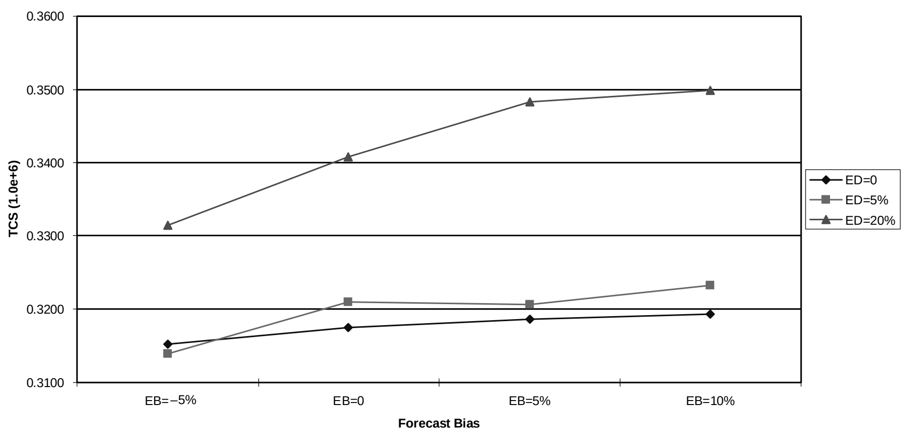
hence, is not provided here. When EB is –5%, the retailers constantly underestimate the demand and incur a high level of shortage cost and backorder cost. As EB increases and gets closer to zero, the backorder cost at the retailers decreases significantly. As EB becomes positive and continues to increase, the retailers gradually overestimate the demand, so the inventory carrying cost becomes the dominant cost component while backorder cost diminishes. Thus, TCR and TC continue to increase as EB increases from 0 to 10%.

The plot of TCS, as given in Figure 2, shows a quite different pattern from that in Figure 1. TCS is the lowest when EB = –5% and increases as EB gets larger. However, the increasing rate is steeper for ED = 20% than those for ED = 0 or 5%. A negative EB means that the retailers' forecasts consistently underestimate the demand and that the supplier does not get as many orders as he should. Therefore, the supplier can satisfy the retailers' orders and, thus, has a lower backorder cost and TCS. As EB becomes larger than zero, the retailers overestimate the demand and place more and more orders to the supplier. Such increased ordering to the supplier pushes TCS higher.

Impact of order commitment period on cost performance

The second research question concerns the relationship between the early order commitment period and cost performance. The ANOVA analysis in Table 5 indicates that OC is the most significant experimental factor. The interactions of both OC*EB and OC*ED are significant as well. Figures 3 and 4 provide the TC plots on various periods of early order commitment, categorized by EB and ED, respectively. Figure 3 shows that the roughly U-shaped TC plots drop significantly as OC increases from 0 to 5 periods, and then gradually increase as OC becomes larger. The increasing rate of TC depends on the level of EB, where EB = 0 has the slowest increase, while

Figure 2: Interaction of forecast bias (EB) and forecast deviation (ED) on total cost for the supplier (TCS).



EB = 10% has the fastest. Table 7 provides the breakdown of three cost performance measures and the internal backorder cost of the supplier (BCS), classified by OC and EB. Recall that BCS is one component in TCS. Both TC and TCS values show a dramatic drop as OC moves from 0 to 5. However, across all levels of EB, the decline of TCS values is especially large and is attributed to the change of the proportion of BCS within TCS. As OC increases from 0 to 5, the proportion of BCS drops from around 50% to 13% (see BCS/TCS ratios in Table 7). That proportion then decreases gradually as OC increases. TCS values continue to decline as OC increases from 5 to 15, but at a much slower rate. As OC reaches 20, TCS increases slightly, and the differences of TCS across different EB levels are marginal. On the other hand, in Table 7 the TCR values are consistently going up as OC increases from 0 to 20, with EB = 10% having the fastest increasing rate and EB = 0 the lowest increasing rate.

Such a difference in cost implication to the supplier and the retailers is the consequence of changes of different cost components. Earlier order commitment made by the retailers allows the supplier to optimize his production decision over a longer planning horizon and better utilize his production capacity. When OC is smaller, the increase in OC has a dramatic impact on the improvement of capacity utilization. As OC increases further, the effect on the improvement of capacity utilization shows diminishing return. For the retailers, however, there are two opposite effects of committing orders earlier. First, a larger OC period helps the supplier improve his capacity utilization, resulting in better services to the retailers. The improved service level helps reduce backorder costs incurred at the retailers and, hence, leads to better performance of the retailers. Second, as OC becomes larger, the retailers will have to make their demand forecasts further into the future and, hence, forecasting accuracy deteriorates. As a result, the orders placed to the supplier become less reliable and cause higher backorder costs and inventory carrying costs to the retailers. Overall, the results show that the second effect dominates the first. This is why the TCR values always increase as OC increases.

Figure 3: Interaction of early order commitment period (OC) and forecast bias (EB) on total supply chain cost (TC).

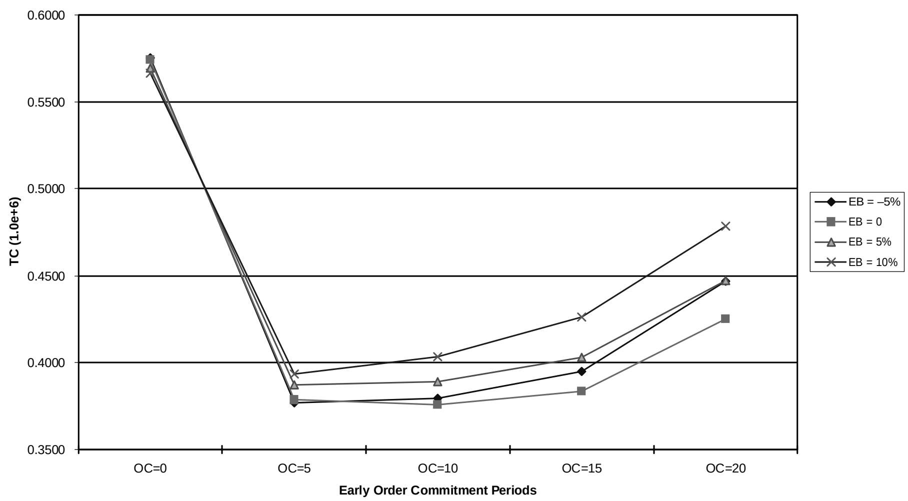


Figure 4: Interaction of early order commitment period (OC) and forecast deviation (ED) on total supply chain cost (TC).

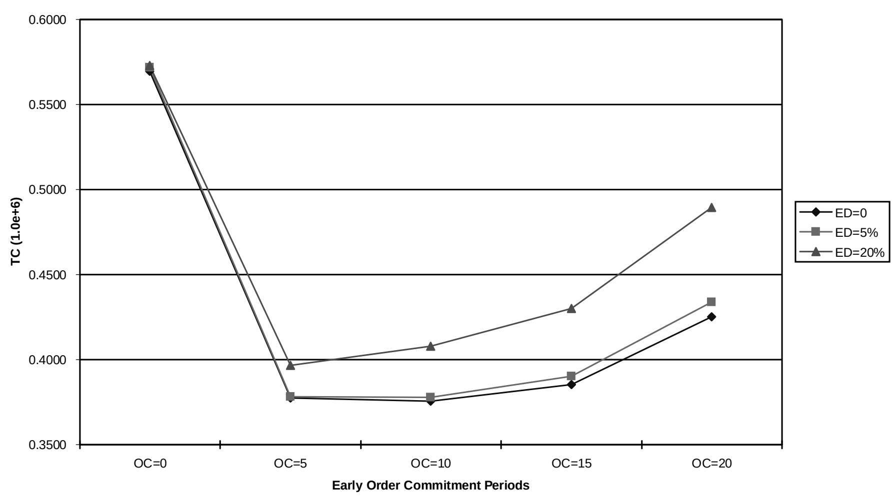


Table 7: Cost performances classified by forecast bias (EB) and early order commitment period (OC).

	EB = –5%	EB = 0	EB = 5%	EB = 10%
TC				
OC = 0	.5751	.5742	.5696	.5663
OC = 5	.3767	.3785	.3871	.3936
OC = 10	.3795	.3756	.3891	.4033
OC = 15	.3949	.3836	.4030	.4260
OC = 20	.4469	.4252	.4470	.4785
TCS				
OC = 0	.8053	.8209	.8206	.8291
OC = 5	.2184	.2221	.2251	.2175
OC = 10	.2007	.2019	.2034	.1992
OC = 15	.1879	.1894	.1967	.1990
OC = 20	.1888	.1979	.1999	.2093
TCR				
OC = 0	.1668	.1655	.1660	.1663
OC = 5	.1856	.1865	.1940	.2039
OC = 10	.1974	.1933	.2054	.2214
OC = 15	.2178	.2050	.2219	.2434
OC = 20	.2689	.2436	.2631	.2913
Internal backorder cost BCS = TCR + TCS – TC				
OC = 0	.3970	.4121	.4170	.4291
OC = 5	.0273	.0301	.0320	.0278
OC = 10	.0186	.0195	.0196	.0172
OC = 15	.0108	.0108	.0156	.0164
OC = 20	.0108	.0163	.0160	.0221
BCS/TCS ratio				
OC = 0	49%	50%	51%	52%
OC = 5	12%	14%	14%	13%
OC = 10	9%	10%	10%	9%
OC = 15	6%	6%	8%	8%
OC = 20	6%	8%	8%	11%

Labels: TC = total supply chain cost, TCS = total cost for the supplier, TCR = total cost for the retailers, BCS = backorder cost for the supplier

Figure 4 provides the profile of the OC*ED interaction on TC. These TC plots are strikingly similar to the TC curves observed in Figure 3. Not only are the shapes similar, but the values of TC at different OC periods in these two figures are close. A cost component analysis of Figure 4 also indicates a very similar pattern to what was discovered for Figure 3. Comparing across three levels of ED in Figure 4, ED = 20% produces the highest TC, while ED = 0 produces the lowest. The TC values drop sharply as OC increases from 0 to 5, then increases gradually afterwards. The proportion of BCS/TCS drops from around 50% to around 14% as OC moves from 0 to 5 periods.

From the above observations about OC, we conclude that in the base case experiment early order commitment is beneficial to the entire supply chain and to the supplier, but at the expense of the retailers. Moreover, the benefits are especially significant as compared to the situation when no early order commitment is made (OC = 0). The savings could be enormous to the supplier and to the supply chain as a whole. However, we also note that the benefits only last for a "feasible" range of OC periods. After the great reduction in the initial stage, TC flattens quickly before it continues to increase as OC is increased further. The greater the forecast errors, whether in terms of EB or ED, the shorter the feasible range of OC periods.

Impact of demand pattern

Our third research question centers on whether demand trends and seasonality affect early order commitment. The Duncan's groupings in Table 6 show that among the three demand patterns, SEA (seasonality without trend) has the lowest TC, while SDT (seasonality with a negative trend) has the highest TC. The performance ranking of the three demand patterns can be explained by the assumption that the supplier has a constant capacity over time.

In the case of SDT, the demand decreases over time. In the earlier periods of the simulation horizon, demand is higher than capacity so that backorders occur. These backorders are carried over to later periods. The demand decreases as time goes on, so there is excess capacity available towards the end of the simulation horizon. The backorders that happened at the beginning of the simulation can now be filled by the excess capacity. Because of the cumulative nature of the backorders, high backorder costs are incurred early and last over a long period of time. Thus, the total cost for SDT is higher.

In the case of SIT, the demand increases over time. Therefore, the demand is lower than the capacity in the earlier periods and, thus, the back orders are lower initially. As time advances, demand becomes higher than the available capacity towards the end of the simulation horizon and, hence, significant backorder costs occur in the later periods. However, there is less accumulation of backorders from earlier periods, so the backorder cost is actually lower for SIT than for SDT.

When the demand is SEA, there is only seasonal variation but not trend. The seasonal variation tends to average out within the cycle periods (14 periods in this case). Therefore, the fixed capacity can accommodate the demand variation much better than when trends are present. The backorder costs and, hence, the total system costs, are lower than those in the cases of SIT and SDT.

Figure 5 presents the TC plots of three demand patterns (DP) across various levels of forecast bias (EB). It shows that EB = 0 results in the lowest level of total system cost regardless of the demand patterns. When EB increases in either the positive or the negative directions, TC increases. The plots also indicate that the TC gaps among the demand patterns are relatively uniform across various levels of EB, hence, the interaction of DP*OC is insignificant. Therefore, either positive or negative forecast bias will increase the total system cost regardless of the demand patterns faced by the retailers. The plots of TC on DP*ED interaction look similar to those in Figure 5 (and hence is not included). The larger the ED value, the higher the TC.

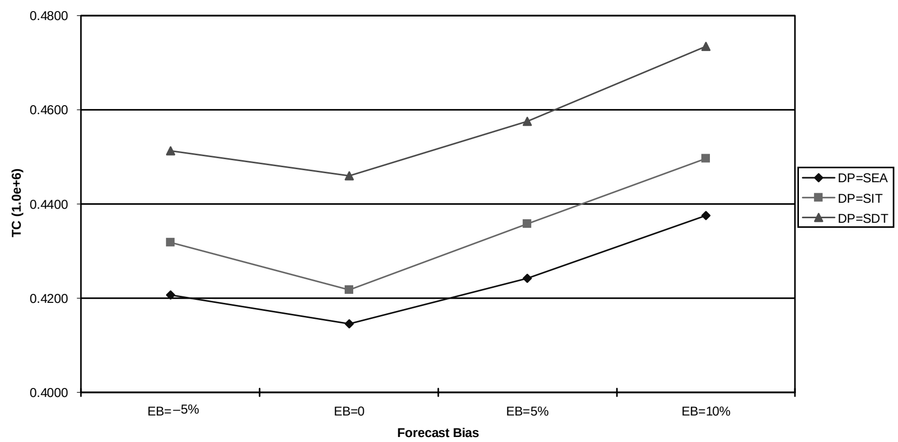
To examine the impact of demand pattern on the benefits of early order commitment, we plot the OC*DP interaction on TC in Figure 6. The TC curves of the three demand patterns all follow the similar shape as shown in Figures 3 and 4 earlier. As OC first increases from 0 to 5 periods, TC decreases dramatically under all three demand patterns. As OC is increased from 5 periods to 10 periods, TC does not show dramatic increase for any of the three demand patterns. When OC is increased further, TC increases very quickly for DP = SDT. The effect is less dramatic with DP = SEA, while the increase is very slight with DP = SIT. Such a difference in the cost change is caused by the capacity imbalances between supply and demand under different demand patterns. When OC increases, there are two opposite effects on the performance of the system. First, as the early order commitment increases, the forecasting accuracy of the retailers deteriorates and, thus, leads to a higher inventory carrying cost and backorder cost for the retailers. The second effect is that the orders placed earlier will help the supplier make better capacity utilization decisions and, thus, reduce the backorder cost for the suppliers. For the SIT demand, the demand increases over time. While there is excess capacity in the early periods, there are more capacity shortages towards the later periods of the simulation horizon. A longer earlier order commitment period helps the supplier to schedule more production when there is excess capacity and, thus, helps to reduce backorders in later periods. This is why a longer earlier order commitment period is more beneficial to the SIT demand.

On the contrary, the SDT demand exceeds capacity in the early periods, but significant capacity shortage and backorders accumulate during the simulation horizon. Committing orders early does not help much in improving capacity utilization and, hence, the first effect becomes dominant. This is why the total cost increases dramatically when OC exceeds 10 periods. For the SEA demand, the imbalance between capacity and demand is not as serious because there is no trend in the demand. The increase in OC does not lead to much improvement in capacity utilization, either. Therefore, TC also increases as OC is increased from 10 to 20 periods. Overall, the results in Figure 6 show that significant cost savings can be achieved for the entire supply chain through early order commitment, and the best OC period seems to be between 5 and 10 periods.

Four Sensitivity Analyses

After the base case experiment was completed, we performed a series of sensitivity analysis experiments to explore whether the findings of the base case still apply in

Figure 5: Total cost performance of forecast bias (EB) under different demand patterns (DP).

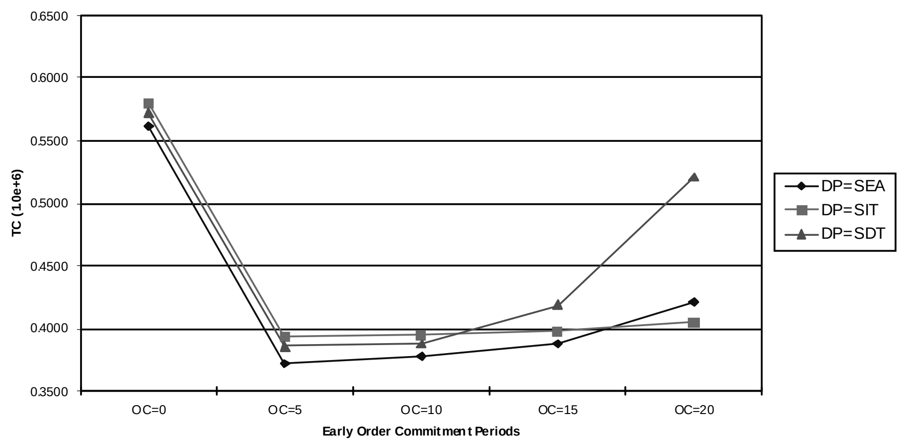


different environments where the operational parameters are changed. We tested four additional factors, one at a time, in the following sequence: cost structure, number of retailers, capacity tightness, and capacity adjustment policy. In each analysis, the experiment repeated the simulation with the same factors and parameter settings used in the base case, except for modifying the new factor of interest.

Cost structure

Though there are many cost components in the performance measure of the TC, we focus on changing two cost items: backorder cost and inventory carrying cost. These two cost items not only affect both the supplier and the retailers, they are also the most dominant cost components in the simulation. We use two levels for each cost item: a 1:5 ratio (denoting Low and High) on backorder cost and a 1:2 ratio (Low and High) on carrying cost. Because the assessment of backorder cost tends to be more subjective and harder to do than that of inventory carrying cost, we give it a higher ratio to reflect a larger range of variation. Therefore, we test four combinations (cases) of these two costs. As summarized in Table 1, Case 1 is the base case featuring Low backorder costs and Low carrying costs. In Case 2, both the backorder costs for the supplier and for the retailers are raised to five times higher than those in the base case, while the carrying costs remain unchanged. On the other hand, the carrying costs for the supplier and the retailers are doubled in Case 3, but the backorder costs stay the same as in the base case. Finally, Case 4 uses both the High backorder costs and the High carrying costs. We discussed the values of these cost parameters with the supply chain manager of the soft drink company, and he believed that these parameters are within a reasonable range. The annual carrying cost for the High carrying cost cases is equivalent to 36% of the item value. The backorder cost per period is equivalent to 5% of the item value per day backordered in the cases with High backorder cost.

Figure 6: Total cost performance of early order commitment (OC) under different demand patterns (DP).

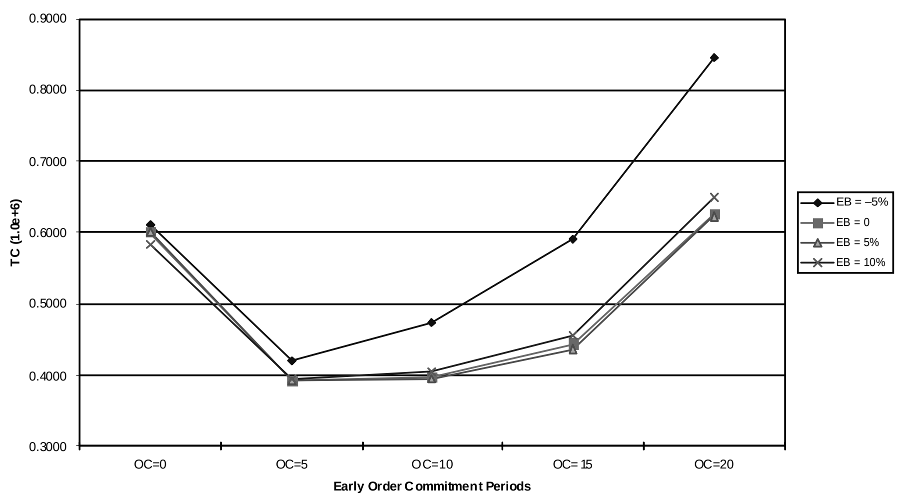


The experimental results from Case 2 show two unique characteristics. First, we found that the TC values at EB = –5% increased drastically after OC exceeds five periods. As shown in Figure 7, the TC plots still follow the U-shape similar to the ones in Figure 3. Because of higher backorder costs, the TC values are all higher than those observed in Figure 3. However, the TC curve associated with EB = –5% has the highest values across all OC periods and shows the steepest cost increase. A further analysis shows that the cost increase at EB = –5% is primarily due to an increase in TCR. As discussed earlier, when EB = –5% the retailers constantly underestimate the demand and incur a high level of shortage and backorder cost. Now that the retailer backorder cost is five times higher, naturally, the TCR goes up drastically.

Second, we found a strong interaction between demand pattern (DP) and OC period. As plotted in Figure 8, the TC curves are similar to those observed in Figure 6, yet quite different in the scale. Though the plots are still U-shaped in Figure 8, the vertical scale shows a much larger upper limit (at 1.1 instead of 0.65 as in Figure 6). The TC curve associated with DP = SDT (negative trend) has a very steep cost increase from OC = 15 to OC = 20 that now dwarfs the TC values at OC = 0. This TC curve is similar to its counterpart in Figure 6 but with a much larger increase of TC. For the TC curves of the other two demand patterns, the costs increase uniformly across all the OC periods with much smaller rates. A detailed data analysis indicates that the TC value at OC = 20 under SDT increases by 94% in comparison to the one in the base case (i.e. on Figure 6). Likewise, the average TCR increases by 151% and average TCS by 61%, respectively. Apparently, a five-time higher backorder cost exacerbates the increase of TCR and, hence, the shape of the TC curve for SDT at OC = 20.

Except for the above two unique characteristics above, the remaining results from Case 2 show very similar patterns to those found in the base case. Furthermore, we found no significant differences between the findings of Case 3 (High

Figure 7: Interaction of early order commitment period (OC) and forecast bias (EB) on total supply chain cost (TC) when backorder costs are five times higher.



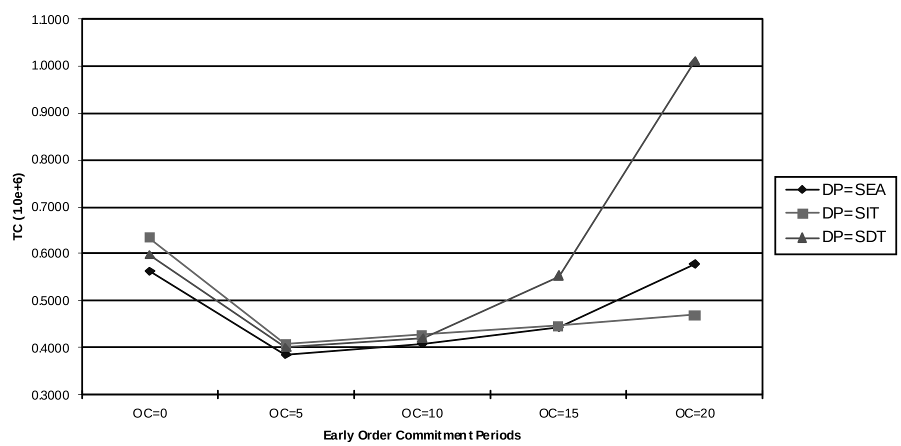
carrying cost but Low backorder cost) and those in the base case. On the other hand, the results of Case 4 (High carrying cost and High backorder cost) give patterns that are a hybrid between those found in Case 2 and in the base case. From these analyses, we conclude that the cost structure does not significantly influence the general conclusions that we made in the base case concerning the impact of early order commitment on the performance of supply chains.

Number of retailers

The second sensitivity analysis was to test the impact of the number of retailers. While the base case used four retailers and a common supplier, here we test two other values of retailers: one and eight. To ensure a fair comparison, we maintain the aggregate demand for all retailers at 4,000 units (1,000 units per retailer * 4 retailers) regardless of the number of retailers used. In the instance of one retailer (NR = 1), we used the average of the four sets of the cost parameters adopted by the four retailers in the base case. When there are 8 retailers (NR = 8), we simply duplicated the four retailers used in the base case.

While most of the results of this sensitivity analysis are very similar to those found in the base case, we note that the number of retailers does significantly influence the cost savings that can be achieved by early order commitment. Figures 9 and 10 show the total supply chain costs under different combinations of early order commitment (OC) and expected bias (EB) for one and eight retailers, respectively. When the results in Figures 3, 9 and 10 are compared, we can see that when there is only one retailer, the total cost is much lower than that in the base case (NR = 4). When there are eight retailers (NR=8), the total cost is much higher than that in the base case. These cost changes are understandable because fewer retailers incur

Figure 8: Total cost performance of early order commitment (OC) under different demand patterns (DP) when backorder costs are five times higher.



lower transportation costs and setup costs, while the carrying costs and backorder costs are less likely to be affected by the number of retailers.

When the cost savings as a result of early order commitment are compared, we can see that the number of retailers significantly influences the cost savings as a result of early order commitments. As the number of retailers increases, the maximum amount of cost savings (i.e., the gap in TC between OC = 0 and OC = 10) that can be achieved through early order commitments increases considerably. Furthermore, the "feasible range" of OC also increases as the number of retailers increase. When more retailers are committing orders earlier, it allows the supplier to "pool" the demands together to reduce the lumpiness of the workload and smooth production.

Capacity tightness

In the base case, the available capacity is set at a constant (Medium) level during the simulation horizon so that the average demand is 80% of the capacity level, equivalent to an 80% capacity utilization. In the third sensitivity analysis, we tested two other levels of capacity utilization—70% (Low) and 90% (High)—by adjusting the capacity level. A lower capacity utilization gives the supplier more cushion to smooth his workload and, hence, reduce backorders. As expected, when capacity utilization is lower, the supplier has much lower TCS due to fewer backorders, whereas the retailer costs (TCR) remain about the same level. Therefore, overall TC values are about 10% lower when the capacity utilization is Low than when it is Medium. The results and TC plots for the Low capacity utilization case are very similar to the findings reported about the base case. We do find that the TC values are still the highest for the demand pattern with negative trend (SDT), but the TC values are very close between SEA and SIT. This indicates that when the supplier has a larger capacity cushion, the supply chain can better cope with a demand that is increasing over time (positive trend).

Figure 9: Interaction of early order commitment period (OC) and forecast bias (EB) on total supply chain cost (TC) with only one retailer (NR = 1).

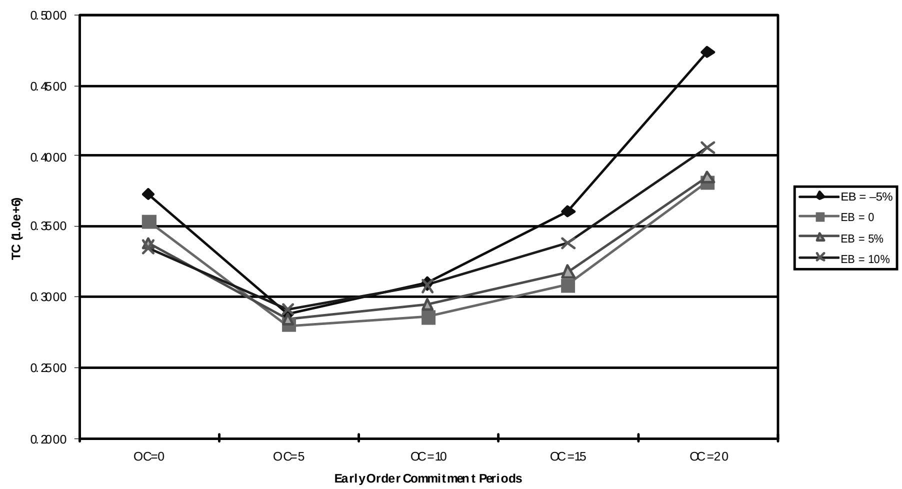
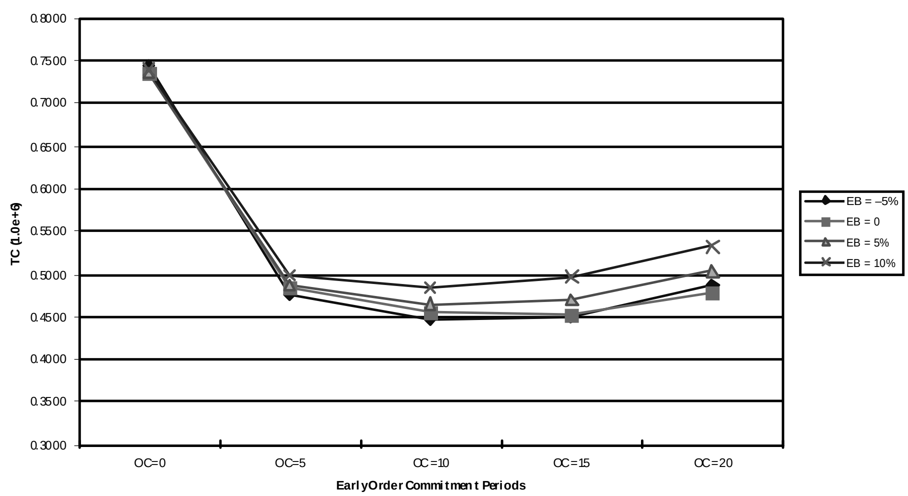


Figure 10: Interaction of early order commitment period (OC) and forecast bias (EB) on total supply chain cost (TC) with eight retailers (NR = 8).



On the other hand, when capacity is tight (Utilization =90%) the TC curves are quite different from those reported earlier in the base case. In Figure 11, the TC curves are plotted against different OC and EB, as in Figure 3 of the base case. The TC plot shows that the costs continuously decline (rather than U-shaped as in Figure 3), but the decline rate is slower as OC increases. Compared to their counterparts in Figure 3, the TC values at OC = 15 and 20 in Figure 11 are about twice as high, while the TC values at OC = 0, 5, and 10 are about three times higher. Following the notion of the feasible range from Figure 3, here we see the feasible range of OC is as long as 20 periods. These observations suggest that when capacity is tight a longer OC would be more helpful in reducing the total system cost. In addition, Figure 11 also shows that the TC values drop consistently as EB increases from –5% to 10%. Compared with Figure 3, where EB = 0 has the lowest TC, EB = 0 in Figure 11 has the second highest TC. The reason for this is that the retailers underestimate the demand when EB = –5%, thus, they face a severe penalty of backorder costs as the supplier cannot produce enough supplies in time due to a tight capacity. On the other hand, the larger the EB value, the higher will be the level of overestimating demand. When the supplier's capacity is tight, the retailers' overstocks reduce the need for ordering from the supplier. The plots of TC on OC*ED for the case of tight capacity show a similar pattern as seen in Figure 11. The plots regarding demand patterns are also similar to the ones observed in the base case.

Capacity policy

In the fourth sensitivity analysis we simulate an environment that is more flexible. Rather than being set at a constant level throughout the simulation horizon as in the base case, we allowed capacity to be adjusted based on the demand generated at each period. To ensure a fair comparison with the base case, we still maintained the capacity utilization at 80%. Note that although the utilization rates are the same, the base case represents an average capacity utilization, while the sensitivity analysis here shows an adjustable capacity that is always 20% higher than the demand of that period. Overall, the TCR values do not change much from the base case, but the TCS values drop 15%, and the TC values drop 3%. All the observations about EB, ED, and OC are very similar to the base case. The only notable difference has to do with the impact of demand pattern. In Figure 12, we plot the TC curves across three demand patterns and four EB values. Compared with Figure 5, its counterpart of the base case, Figure 12 shows a similar pattern in which EB=0 still has the lowest TC and EB=10% the highest. However, while SDT demand still has the highest TC, the lowest TC curve is with SIT demand in Figure 12. In contrast, the lowest TC was with SEA demand in Figure 5.

Upon close examination of the component costs under different demand patterns, we found that the total cost under SIT demand is the lowest mainly because of lower ordering costs incurred by the retailers (OCR) and by the supplier (OCS) under SIT. The scenario is caused by the effect of the initial inventory. Under SIT, the demand at the beginning simulation periods is lower. Thus, the initial inventory can usually cover demands for more periods, and fewer orders are placed during the earlier periods. When the demand is higher in later periods of the simulation,

Figure 11: Interaction of early order commitment period (OC) and forecast bias (EB) on total supply chain cost (TC) when capacity is tight (Utilization = 90%).

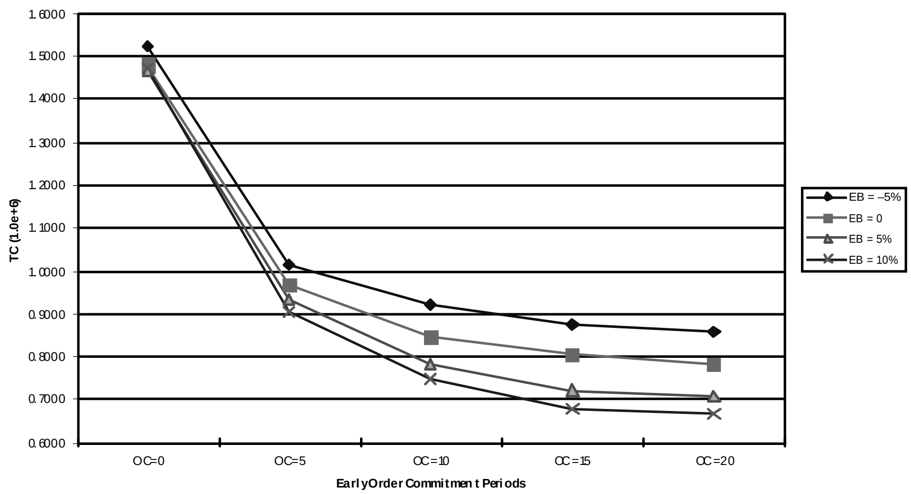
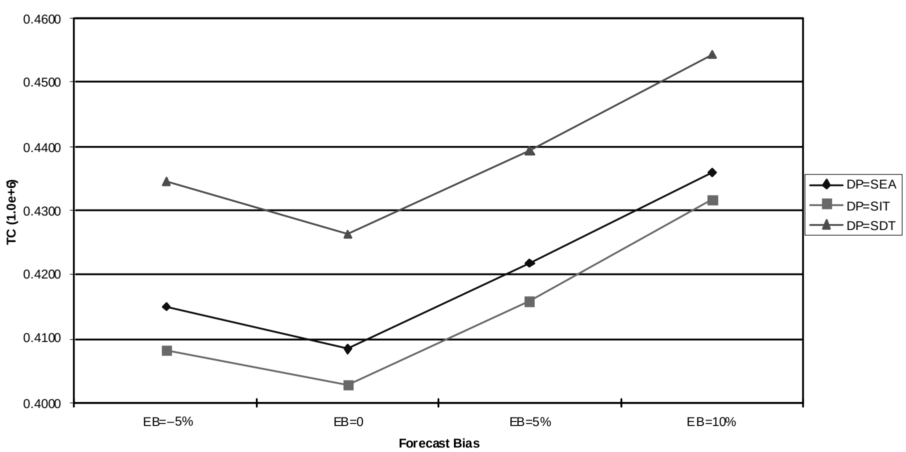


Figure 12: Total cost performance of forecast bias (EB) under different demand patterns (DP) when capacity is adjustable.



more orders are placed. The net result is that the ordering frequency is the lowest under SIT demand and, hence, the lowest ordering cost. When the supplier's capacity can be adjusted, the backorder costs for both the supplier and retailers are low, and the OCR and OCS are the dominating components in the TC. Therefore, the total supply chain cost under SIT is lower than that under SEA when the capacity can be adjusted. When the capacity is fixed, however, backorder cost becomes the dominating cost component. Since there are significantly higher backorder costs under SIT than under SEA, total cost under SIT is higher when capacity is fixed. This is what we observed in the base case.

SUMMARY AND CONCLUSIONS

This research studies the value of practicing early order commitment in a supply chain setting. It also investigates the impact of forecasting errors on the selection of early order commitment periods. After visiting a soft drink bottling plant and consulting its managers, we developed a computer simulation to study a two-stage supply chain with one capacitated supplier who supplies the same product to multiple retailers. We designed a base case experiment to address three core research questions surrounding the value of early order commitment, the impact of forecast error, and the impact of demand pattern. We then examined the robustness of the findings of the base case via four sensitivity analyses by changing cost structure, number of retailers, capacity utilization, and capacity adjustment policy. Our experiments led to the following main findings and managerial implications:

1. To improve the total system cost of the supply chain, both forecast bias (EB) and forecast deviation (ED) are important factors to control, whereas the increase rate of forecast deviation over time is an insignificant factor. A larger forecast deviation would worsen the cost performances of both the supplier and the retailers. On the other hand, the impact of forecast bias has different cost implications to the supplier and the retailers. A negative forecast bias causes underestimation of the demand and, hence, high backorders for the retailers, while the supplier's cost remains low.

2. Early order commitment from the retailers to the supplier can reduce total system cost in the supply chain, but the benefits are only valid within a feasible range of order commitment (OC) periods. Greater benefits tend to occur when the OC value is small, then the savings diminish quickly as OC increases. In addition, the larger the forecast error, whether in the form of bias or deviation, the shorter the feasible range of OC. Therefore, when demand uncertainty is high or when a retailer's forecasting capability is questionable, the retailer should not make an order commitment too early (but it is still worthwhile to do for a short period).

3. The benefits of early order commitment are different for the supply chain members involved. To a supplier, the longer the order commitment periods, the easier to plan for production and, hence, the more cost savings can be gained. For the retailers and the whole supply chain, judicious use of early order commitment is required. Such a finding suggests that for the

well-being of the entire supply chain it may be worthwhile for the retailers to take a “sacrifice.” The sacrifice can be either losing a certain degree of flexibility of “waiting until the last minute to place an order” or bearing a slightly increased cost. The savings of adopting earlier order commitment are more easily attained when the supplier and retailers are owned by the same corporation or are engaged in some gain-sharing programs.

4. The presence of trend in the demand increases the total system cost in a supply chain. A negative trend causes a higher total system cost than does a positive trend. Adopting a short OC period would greatly reduce total supply chain cost regardless of the demand pattern. However, a longer OC period is beneficial to the cost performance under the demand with a positive trend but is detrimental when the demand has a negative trend.
5. Though the change of cost structure does not alter the patterns of the cost performances in general, it certainly affects the selection of OC periods for some occasions. We found that higher unit backorder costs had a greater impact on the findings than higher unit inventory carrying costs. High backorder costs exacerbate the situations in which a retailer underestimates the demand but commits orders early. These situations tend to happen when there is a negative forecast bias or there is a negative trend in the demand.
6. Given the same aggregate demand, the more retailers sharing one supplier, the more valuable for the supply chain to practice early order commitment.
7. On the other hand, the findings of the base case are robust when the capacity cushion of the common supplier is raised. Likewise, the findings are not much different from those of the base case when capacity can be adjusted periodically. On the other hand, when the capacity cushion is reduced, the value of committing orders earlier increases, and the feasible range of OC becomes wider than that in the base case. Moreover, when capacity is tight, a larger positive forecast bias tends to help reduce costs due to overestimating the demand.

In conclusion, these findings suggest that early order commitment can be a fruitful avenue for enhancing supply chain coordination and reducing total system inefficiency. They also shed light on the complex interactions between early order commitment and forecast errors. Given the fact that little research has been done to address the use of early order commitment, the findings of this research may provide helpful guidelines for managers who are seeking new opportunities for supply chain integration.

Clearly, these findings are only valid for the environmental settings in which we conducted the study and the data we tested in the experiment. There are several areas for future research: First, the structure of the supply chain can be expanded to more tiers rather than just one tier as studied in this paper. Second, in this study we assumed that the supplier uses a particular capacitated lot-sizing rule to make his production decision and the retailers use EOQ to make their inventory decisions. Changing the ordering and production rules may lead to new findings.

Third, we only focused on various types of costs in the supply chain. It would be interesting to extend the research to include pricing discounts and other forms of incentives to entice retailers to commit orders earlier. Finally, empirical research that examines the practice of early order commitment in a supply chain setting is in great need. [Received: January 10, 2000. Accepted: March 1, 2002].

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