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Improving the supply chain performance: use of forecasting models versus early order commitments

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This paper evaluates the impact of forecasting models and early order commitment in a supply chain with one capacitated manufacturer and four retailers under demand uncertainty. Computer simulation models were used to simulate different demand forecasting and inventory replenishment decisions by the retailers as well as production decisions by the manufacturer under a variety of demand patterns and capacity tightness scenarios. This study found that early order commitments significantly affected the total costs and service levels, to various degrees, for the manufacturer and the retailers, suggesting that the benefits of early order commitment could be influenced by a combination of forecasting models, demand patterns and capacity tightness.

1. Introduction

One of the most challenging tasks in supply chain management is to coordinate separate functional activities, including logistics, information sharing and material management, across a wide spectrum of business organizations and geographical locations. Until recently, most businesses have focused primarily on improving their internal operations to serve better their immediate customers, and have placed little attention on other organizations along the supply chain. The traditional, piecemeal approach to managing a supply chain has been, in part, a result of limited exchange of timely and accurate information among business partners. The advances in technology and globalization of markets have fostered the emergence of an integrated systems approach to achieving the maximum efficiency of a supply chain. In particular, new information technology has made possible real-time, online communications among all constituencies within a supply chain. Information technology has become supply chain 'enablers' that can substantially improve communication, and reduce lead-time and non-value-added activities (Handfield and Nichols 1999).

The purpose of this study is to investigate the impact of forecasting model selection and early order commitment on the supply chain performance. We consider a decentralized supply chain consisting of four retailers and a single manufacturer— a business scenario based on one of our recent research case studies. In this decentralized supply chain, the retailers do not make their forecast demand available to the remainder of the supply chain. By comparing the performance of the supply chain under different scenarios of demand patterns and capacity tightness, we provide insights to minimize the negative impact of demand uncertainty in a supply

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chain. This study comes at a time when various types of forecasting models or order coordination are being experimented with in many industries, but their success and failure are not yet fully understood. In addition to providing managerial insights into questions that arise in this context, our findings can also serve as building blocks for future work in this emerging area of research.

2. Literature review

As supply chains are becoming more complex in today's competitive, ever-changing business environment, the supply process can easily become fragmented and evolve into a series of individual decisions by separate business organizations. Demand forecasts are necessary but inadequate for meeting the needs of customers responsively, given long lead times for ordering and supplying goods and material within a supply chain. As most retailers are not able to forecast their customers' demand with certainty, any errors in the retailers' forecasts are passed to their 'upstream' suppliers in the form of distorted orders. The distorted orders tend to amplify the volatility of demands and thus increase inventories in the supply chain. For example, when the orders for new computers slow down slightly, the chip makers will see a steep drop in demand and the chip equipment makers will feel an even more drastic drop in demand. This phenomenon of volatility amplification is widely known as the 'bullwhip effect' in supply chain management literature (Lee *et al*. 1997).

Many recent studies have supported coordination among various members of a supply chain, such as suppliers, manufacturers, distributors, wholesalers and retailers, to achieve better supply chain performance while minimizing the bullwhip effect. A number of demand patterns and supply chain configurations have also been investigated. See, for example, Lee *et al*. (2000), Chen *et al*. (1998) and Chen *et al*. (2000). Most of the studies of the bullwhip effect have focused on the distortions in demand information as one proceeded upstream in the supply chain. Although these studies provided insights to the variations in quantity for materials or goods, the financial impact of the inefficiencies of the bullwhip effect was seldom explored. Metters (1997) studied the impact of the bullwhip effect on profitability by establishing an empirical lower bound on the cost excess of the bullwhip effect. His results indicated that the importance of the bullwhip effect to a firm differed greatly depending on the specific business environments. He showed that eliminating the bullwhip effect could increase product profitability by 10%–30% in many cases. Although these results expressed the significance of the bullwhip effect in monetary terms, he did not include retailers in the study and just generated the demand for the capacitated supplier using demand functions with different variations. Furthermore, he did not consider ordering cost, transportation cost and production set-up cost.

Using a simulation model, Johnson *et al*. (1999) examined the impact of Vendor Managed Inventory (VMI) in less-than-ideal environments, such as those with high demand volatility, partial adoption of VMI, and limited manufacturing capacity. They found that the operational benefits associated with VMI were very compelling. They showed that the VMI approach greatly reduced inventories for all participants in the supply chain without compromising service. However, they assumed that VMI only involved the reduction in ordering frequency from the retailers to the supplier and they did not measure the benefit of VMI in terms of cost savings. Actually, VMI can involve many other important issues, such as coordination and integration of decisions in inventory replenishment, transportation and production.

The literature review on supply chain management suggests that many prior studies have demonstrated the complex dynamics in the supply chain. However, most of these studies have not provided enough insights and guidelines for minimizing the negative impact of demand uncertainty in a supply chain. In this study, we examine the interactions between the choice of forecasting models and early order commitment by retailers under a variety of demand patterns and capacity constraints. Since the bullwhip effect has a more drastic impact on the upstream suppliers than the downstream users (such as the retailers), early order commitment from the downstream users and better forecasts should enable the upstream suppliers to smooth production, better utilize resources, and ultimately reduce costs in the supply chain. The major objective of this study is to investigate the effect of these decisions on the cost and service performance of the manufacturer, the retailers, and the entire supply chain.

3. Research hypotheses

While early order commitment allows the manufacturer to plan ahead and better use its capacity to reduce costs and improve service levels for the supply chain, the benefits and effectiveness of early order commitment could be dependent on the prevailing demand patterns, available capacity, and the corresponding forecasting methods used. Therefore, we propose using a simulation model to address the following research hypotheses.

Hypothesis 1: Early order commitment by the retailers significantly reduces the total costs for all members in the supply chain.
Hypothesis 2: Early order commitment by the retailers significantly improves the service levels for all members in the supply chain.
Hypothesis 3: The benefits of early order commitment are significantly different for different demand patterns and forecasting models.
Hypothesis 4: The benefits of early order commitment are significantly different for different capacity tightness and forecasting models.

4. The simulation environment

4.1. *Background*

Our simulation design — which mimicked one of our recent research case studies and so provided more realistic cost structure and demand characteristics — involved a simple, two-stage supply chain consisting of one manufacturer and four retailers. The manufacturer had a capacitated facility producing a single product for the four retailers. No explicit production lead times are considered here because a constant lead time would not change the conclusion in any way. However, the actual manufacturing lead time, as a result of insufficient capacity, would be implicitly determined in the manufacturer's production planning decision. The average customer demand per day for each retailer was 1000 units. Retailers replenished their inventories from the manufacturer by placing orders directly to the manufacturer. As a result, the manufacturer needed to maintain an average production rate of 4000 units per day for this product. The lead time for the retailers to place an order to the manufacturer varied depending on the use of early order commitment, a factor to be examined in the simulation experiment.

The shipments of products were delivered directly from the manufacturer to the retailers by trucks. The transportation lead time from the manufacturer to each retailer was one day. Since the truckload was large enough (or, equivalently, the product was small enough in size and weight), a shipment to any one of the four retailers could be completed by a single truck. When a retailer placed an order to the manufacturer, a fixed order processing cost ($100 per order) was incurred. Because only one truck was needed for each order delivery, the actual ordering cost for a retailer was the sum of the single truck transportation cost and the fixed order processing cost. Transportation costs were $450, $255, $331 and $553, respectively, for retailers 1, 2, 3 and 4, depending on the travelling distance.

The production set-up cost of the manufacturer was $1000 per set-up. The inventory carrying costs per unit per day (h) for the manufacturer and the retailers depended on their natural ordering cycles, which are the average numbers of periods covered by an economic ordering quantity (EOQ). They are assumed to be four days for the purpose of this study. Assuming the inventory cost per year was 36.5% of the value of the product, the unit product value could be stated as $365h/36.5\% = 1000h$. We further assumed that the unit backorder cost per day was 5% of the product value. Thus, the backorder costs per unit per day for the manufacturer and the retailers were 50 times their corresponding inventory carrying cost per day. A relatively high backorder cost would not significantly affect the total costs of the supply chain since the possibility of stockout had been rare.

The length of the simulation run (410 days in this study) was selected in such a way that the start up and termination effect would be minimized. The first 50 days were used to estimate the initial parameters for the forecasting models, and the last 10 days were excluded from the performance measure calculations to eliminate any unusual inventory situation towards the end of the simulation run. Therefore, the final performance measures were calculated based on 350 simulation days (from days 51 to 400) of operations. Furthermore, in order to avoid possible backorder for the retailers during the first few days immediately following the 50th day, sufficient initial inventory was assumed for each retailer. In this study, we set the initial inventory at day 51 for the ith retailer at $(14 + i) \times 1000$ ($i = 1, 2, 3, 4$). The different initial inventories are used to avoid all retailers placing the first order at the same time. Our preliminary simulation runs also suggested that such a provision of initial inventories would ensure that each retailer was sufficiently stocked for the following few days after day 51. The simulation procedure consisted of three phases to be discussed below.

4.2. *Phase I: generating randomized demand and production capacity*

The first phase of the simulation generated demands for all the retailers and the available production capacity for the manufacturer. In particular, demand for each retailer was generated by a corresponding demand generator given in Zhao and Lee (1993):

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

where

$Demand_t$	is the demand in day t ($t = 1, 2, \ldots, 410$),
$snormal()$	is a standard normal random number generator,
$SeasonCycle$	$= 7$ for demand varying weekly.

The other parameters (*base*, *slope*, *season*, *noise*) were characteristic parameters for the demand generators, among which base was selected to ensure that the average demand was approximately 1000 units (see table 1). Because there was a normal variate in the demand generation function, the demand generated might take a negative value. We eliminated this possibility by restricting the value produced by the standard normal random number generator to between -3.0 and $+3.0$.

Four demand generators were used: CON produced demand with no trend or seasonality; SEA had only seasonal fluctuation; SIT had seasonal fluctuation and a positive trend; and finally, SDT had seasonal fluctuation and a negative trend. Five demand patterns (DP) representing different combinations of demand generators for the four retailers were used in this study. When the demand patterns of ICON, ISEA, ISIT and ISDT were used, identical demand generators (CON, SEA, SIT and SDT, respectively) were used for all four retailers to generate their demands. When the demand pattern was set to MIX, different demand generators were used for the four retailers to generate their demand.

Without loss of generality, the capacity requirement for each unit of product was assumed to be one; that is, one unit of resource was required by the manufacturer to produce exactly one unit of product. This assumption would simplify the interpretation of the findings because the demand of the product could always be measured by the same amount of resources needed to produce the product. Once 410 days of demands for all retailers had been generated, the total capacity of the manufacturer was simply the total demand of all retailers over the same period of time. The manufacturer's available capacity was assumed to be constant and was equal to the total demand multiplied by the capacity tightness factor.

4.3. *Phase II: retailers' ordering decisions*

The planning horizon of the purchasing plan for a retailer was 16 days, four times the natural ordering cycle, and the re-planning periodicity was set to one day. Based on the demand forecasts, a retailer decided when and how many units to order from the manufacturer during the 16 periods by using the economic order quantity (EOQ) policy. The retailer would place firm orders for the first (EOC + 1) days, where EOC

	Characteristics of demand generators			
Demand generator	Base	Slope	Season	Noise
CON	1000	0	0	100
SEA	1000	0	200	100
SIT	551	2	200	100
SDT	1449	−2	200	100
	Demand generators for demand patterns			
Demand pattern	Retailer 1	Retailer 2	Retailer 3	Retailer 4
ICON	CON	CON	CON	CON
ISEA	SEA	SEA	SEA	SEA
ISIT	SIT	SIT	SIT	SIT
ISDT	SDT	SDT	SDT	SDT
MIX	CON	SEA	SIT	DIT

Table 1. Demand generators and demand patterns.

was the level of early order commitment (number of days ahead of actual demand) and one day was added here to compensate for the transportation lead time. These firm orders were considered 'frozen' and could not be changed.

Since the re-planning interval was one day, one day later a retailer needs to calculate the net requirements for the remaining (16 – EOC) 'free' days. If an order for the first free day was needed, this order would be placed (and committed) to the manufacturer. Orders for the rest of the free days were not placed and could be updated in the next planning cycle. For example, when EOC = 5, the retailer must place the order six days in advance based on forecasts, whereas the manufacturer must deliver the product five days later and this delivery would arrive at the retailer one more day later due to the transportation lead time. Then, at the end of the day, the actual customer demand was realized. The retailer filled the customer's order (plus backorders if any) by on-hand inventory and any shortages would become backorders.

4.4. *Phase III: manufacturer's production and delivery decision*

In our simulation experiment, the manufacturer applied a single-item, capacitated lot-sizing rule, as in Chung and Lin (1988), for planning its production activities. The manufacturer received orders from four different retailers and made production planning decisions based on the available information. At the end of each day, and after the current day's production was completed, the manufacturer made shipping decisions from its on-hand inventory. The manufacturer filled each retailer's order (plus backorder if any) if on-hand inventory was sufficient to fill all retailers' orders and backorders. If on-hand inventory was insufficient, each retailer would be allocated by a quota proportional to its order (plus backorder if any) and any shortages would become backorders to be filled later.

When a retailer placed an order, the retailer was responsible for the transportation cost of that shipment, regardless of whether a portion of the shipment was only to satisfy the backorder of previous orders. If the retailer did not place an order and the shipment to the retailer was to satisfy the backorders of previous orders, the manufacturer would pay for the transportation cost of the current shipment.

This process was repeated until ordering, production and delivery decisions were developed for all 410 days. After the entire simulation run was completed, all cost items were calculated for the retailers and the manufacturer. The total cost (including inventory, order processing and set-up, backorder and transportation) and customer service level would be used to measure the performance of the supply chain. As indicated earlier, all performance measures were only calculated with the data from days 51 to 400.

5. Experimental design

5.1. *Model parameters*

A major advantage of using computer simulation models is to allow many parameters to vary in different simulation settings. There were two major groups of model parameters in this simulation experiment. The first group was the 'environmental factors' or 'operating conditions' of the systems, which included demand pattern (DP) and capacity tightness (CT). The second group was the decision parameters, which included the forecasting model (FM) and early order commitment (EOC).

As indicated earlier, a total of five demand patterns (ICON, ISEA, ISIT, ISDT, MIX) representing the different combinations of demand generators were used in this study. Capacity Tightness (CT) referred to how tight the manufacturer's production capacity was relative to the demand, and was calculated as the total available capacity divided by the total demand to be satisfied. Three levels of capacity tightness, i.e. 'low' (1.33), 'medium' (1.18) and 'high' (1.05), were used. They corresponded to the utilization of resource of 75%, 85% and 95%, respectively.

Three commonly used forecasting models (FM): the naive (NAV), the simple moving average (SMA), and the Winter's model (WIN), were investigated here. To provide a benchmark for comparison, we also included the case where there was no uncertainty; that is, when FM = ACT so that the actual demands in the future days were known and thus the forecasts were perfect.

Early order commitment (EOC) referred to the number of days in advance the retailers were willing to place orders to the manufacturer after considering the normal lead time. Five cases of EOC (0,2,4,6,8) were examined. When EOC was zero, there was no early order commitment between the retailers and the manufacturer. Otherwise, there was an early order commitment from the retailers, as they would place orders EOC days before the delivery date. For example, when EOC was 2, the retailer would place orders two more days ahead of delivery date. A larger EOC value was expected to allow the manufacturer to make more efficient use of its production capacity, but it might also increase the forecasting errors when the retailers must forecast demand and commit orders for a longer period of time.

5.2. *Performance measures*

The following criteria were used as the dependent variables of the experimental design to measure the supply chain performance.

- Total cost for the retailers (TCR). Sum of the ordering cost (including transportation cost), inventory carrying cost and backorder cost.
- Total cost for the manufacturer (TCM). Sum of the set-up cost, transportation cost (for backorder deliveries, if any), inventory carrying cost, and backorder cost.
- Total cost for the entire supply chain (TC). Sum of the TCR and TCM, minus backorder cost paid by the manufacturer to retailers (as it was only an internal cost within the entire supply chain and not actually incurred).
- The service level of the manufacturer (SLM). Percentage of retailers' orders satisfied through the available inventory of the manufacturer. It served as an internal service performance measure within the supply chain.
- The customer service level of the retailers (SLR). Percentage of customer demand satisfied through the available inventory of the retailers. It was averaged for all 350 simulation days and the four retailers. SLR could be considered as the actual service performance of the entire supply chain.

6. Results and analysis

For each combination of the independent variables (FM, EOC, DP and CT), five simulation runs were conducted to reduce the effects of the random variates; thus, a total of $5 \times 3 \times 4 \times 5 \times 5 = 1500$ simulation runs were conducted. The output from the simulation experiments was analysed using the SAS analysis of variance (ANOVA) procedure and Duncan's test.

To meet the ANOVA assumptions of normality, independence and equal variance of the errors, inverse square-root transformations were made to TC (i.e. 1/sqrt(TC)) and TCR (i.e. 1/sqrt(TCR)); a square-root transformation was made to TCM (i.e. sqrt(TCM)), and square transformations were made to SLM (i.e. SLM^2) and SLR (i.e. SLR^2). These transformations were suggested by the SAS package based on the result of residual analysis.

ANOVA results in table 2 showed that, at the 0.05 level of significance, the forecasting model (FM) and early order commitment (EOC) and their interactions had significant effects on all supply chain performance measures, thus deserving detailed analyses of the variables involved.

6.1. *Effects of EOC on total cost and service level*

How did EOC affect the supply chain performance? As shown in table 3, regardless of the choice of forecasting models, placing orders earlier (a larger EOC value) seemed to be beneficial to both manufacturer and retailers in terms of cost reduction. Using the lowest cost as the base index at 100, the average total cost for the entire supply chain as well as for the retailers could be as high as 145 when there was no early order commitment. The cost savings for the manufacturer were even higher, as the total cost could be as high as 197. Ranking of the total cost values by Duncan's multiple range test showed there was significant evidence to support Hypothesis 1, suggesting that the use of early order commitment would reduce the total cost for the manufacturer, retailers, and the supply chain.

While a larger EOC value would also lead to a higher service level to the manufacturer, it did not necessarily lead to a higher service level for the retailers. In fact, other than the case of perfect forecast (FM = ACT), which rarely happens in real life, a larger EOC value actually resulted in a slightly lower service level for the retailers. However, the differences in service levels were often very small and not statistically significant. The results made intuitive sense. When the retailers chose FM = NAV, SMA or WIN with possible forecasting errors and when they place orders earlier, they would have to determine the order quantity based on less accurate forecasts, and thus the service level of the retailers was reduced.

The Duncan's rankings showed that a larger EOC usually resulted in a statistically significant lower TC, TCM, TCR and a higher SLM. However, it also resulted in a decreasing service level for the retailers most of the time. Therefore, Hypothesis 2 of this study could only be supported under certain conditions.

The performance improvements as a result of using early order commitment were found to be significantly different for those forecasting models examined here. A larger early order commitment value (e.g. EOC = 8 versus EOC = 0) produced the largest total cost improvement when the NAV method was used, followed by WIN, SMA and ACT. The differences in the benefits of using early order commitment under different forecasting models were caused by the forecast accuracy of the forecasting models. Our results showed that ACT was the perfect forecasting model with no forecasting error and NAV had the largest forecasting error. If the total cost was initially very high, due to a large forecasting error, a larger value of EOC could reduce the total cost, providing a high relative value of early order commitment. However, if the forecast was quite accurate to begin with and the total cost was relatively low even without any early order commitment, the possibility to reduce the

	Performance measures									
	TC(1)		TCM(2)		TCR(3)		SLM(4)		SLR(5)	
Source	F Value	Pr > F	F Value	Pr > F	F Value	Pr > F	F Value	Pr > F	F Value	Pr > F
DP	42706.88	0.0001	56914.64	0.0001	52199.16	0.0001	3563.37	0.0001	19873.84	0.0001
CT	52469.09	0.0001	87920.61	0.0001	35636.88	0.0001	8399.53	0.0001	16374.80	0.0001
DP × CT	12488.14	0.0001	24935.14	0.0001	14601.87	0.0001	702.82	0.0001	5876.72	0.0001
FM	1165.37	0.0001	258.77	0.0001	2800.61	0.0001	434.43	0.0001	4154.99	0.0001
DP × FM	99.72	0.0001	22.71	0.0001	203.02	0.0001	18.47	0.0001	144.12	0.0001
CT × FM	109.00	0.0001	2.25	0.0365	205.65	0.0001	14.50	0.0001	74.31	0.0001
DP × CT × FM	44.64	0.0001	6.21	0.0001	69.07	0.0001	1.49	0.0594	26.09	0.0001
EOC	970.16	0.0001	8966.48	0.0001	506.17	0.0001	11812.16	0.0001	265.89	0.0001
DP × EOC	25.96	0.0001	53.55	0.0001	199.11	0.0001	208.44	0.0001	55.99	0.0001
CT × EOC	88.30	0.0001	46.76	0.0001	163.53	0.0001	112.58	0.0001	59.22	0.0001
DP × CT × EOC	55.57	0.0001	34.36	0.0001	80.95	0.0001	64.06	0.0001	13.07	0.0001
FM × EOC	29.32	0.0001	33.20	0.0001	49.20	0.0001	30.40	0.0001	210.43	0.0001
DP × FM × EOC	8.93	0.0001	3.76	0.0001	11.81	0.0001	3.27	0.0001	19.75	0.0001
CT × FM × EOC	7.91	0.0001	1.11	0.3227	12.71	0.0001	3.01	0.0001	4.24	0.0001
DP × CT × FM × EOC	3.57	0.0001	0.46	1.0000	5.19	0.0001	0.70	0.9877	2.44	0.0001

(1) Based on residual analysis and suggestion by SAS, the inverse square-root transformation of TC (i.e. 1/sqrt(TC)) was made to satisfy the assumptions of ANOVA.

(2) Based on residual analysis and suggestion by SAS, the square-root transformation of TCM (i.e. sqrt(TCM)) was made to satisfy the assumptions of ANOVA.

(3) Based on residual analysis and suggestion by SAS, the inverse square-root transformation of TCR (i.e. 1/sqrt(TCR)) was made to satisfy the assumptions of ANOVA.

(4) Based on residual analysis and suggestion by SAS, the square transformation of SLM (i.e. SLM^2) was made to satisfy the assumptions of ANOVA.

(5) Based on residual analysis and suggestion by SAS, the square transformation of SLR (i.e. SLR^2) was made to satisfy the assumptions of ANOVA.

Table 2. Selected ANOVA results.

Model parameters		Performance measures									
		TC		TCM		TCR		SLM		SLR	
FM	EOC	RTC(1)	RANK(3)	RTCM(1)	RANK(3)	RTCR(1)	RANK(3)	SLM(2)	RANK(3)	SLR(2)	RANK(3)
ACT	0	142	5	176	5	142	5	68.64	5	98.06	5
	2	124	4	120	4	126	4	87.30	4	98.47	1~4
	4	116	3	106	3	118	3	93.41	3	98.54	1~4
	6	115	2	105	2	117	2	93.80	2	98.55	1~4
	8	112	1	101	1	114	1	94.39	1	98.57	1~4
NAV	0	145	5	197	5	145	5	67.29	5	97.62	1
	2	130	4	144	4	132	4	81.35	4	96.20	4~5
	4	119	3	121	3	120	3	88.17	3	96.58	2~3
	6	109	2	108	2	110	2	91.52	2	96.74	2~3
	8	100	1	100	1	100	1	92.22	1	96.17	4~5
SMA	0	142	5	182	5	143	5	69.65	5	98.03	1
	2	125	4	127	4	128	4	87.78	4	97.76	2~4
	4	118	3	114	3	120	3	92.41	3	97.87	2~4
	6	114	2	109	2	116	2	93.62	2	97.67	2~4
	8	108	1	102	1	110	1	94.55	1	96.77	5
WIN	0	143	5	182	5	144	5	70.53	5	98.15	2~3
	2	123	4	124	4	125	4	87.79	4	98.26	1
	4	116	3	112	3	119	3	93.10	3	98.14	2~3
	6	115	2	109	2	117	2	93.84	2	98.05	4
	8	108	1	102	1	110	1	94.71	1	97.97	5

(1) RTC, RTCM and RTCR represent relative total costs of the entire supply chain, the manufacturer and retailers respectively. The lowest total cost among different model parameters is set at 100.

(2) SLM and SLR represent the service levels for the manufacturer and retailers respectively. It is the percentage of orders or demands filled from on-hand inventory.

(3) RANK represents the rank of the values of an independent variable obtained using Duncan's multiple range test at the .05 level of significance.

Table 3. Performance of EOC under different forecasting models.

total cost was small. Therefore, the relative value of early order commitment was reduced. The cost savings of placing an order 8 days in advance versus no early order commitment could be over 100%. Furthermore, the naive model in combination with EOC = 8 days produced the lowest total cost for the supply chain among all simulated scenarios. The total cost savings from using early order commitment could be as high as 58% when the naive model was used to forecast demands with decreasing trend. When the retailers faced mixed demands or identical demands without trend, the total cost savings were generally much lower and any early order commitment might not benefit the retailers at all.

6.2. *Interactions among EOC, demand pattern, and forecasting model*

Referring to the ANOVA results in table 2, the three-way interaction DP $\times$ FM $\times$ EOC had significant effects (p-values < 0.0001) on all five performance measures. Subsequent analyses were conducted to isolate the effects of each combination of the independent variables and the results were summarized and reported here. While not shown here, the detailed performance results of EOC under different forecasting models for different demand patterns are available from the authors upon request.

An examination of the detailed analyses revealed that the demand patterns would significantly influence the performance of forecasting models under different EOC values. When there was no trend in the demand (DP = ICON, ISEA or MIX), a perfect forecast (FM = ACT) always produced a lower total cost (TC) than other forecasting models regardless of the EOC values. The forecasting models with a higher forecasting accuracy generally performed better when measured by TC, suggesting that the total cost of the supply chain was usually improved when the retailers placed orders a few days in advance to the manufacturer. However, a further increase in the EOC might eventually increase the total cost.

When there were trends in the demands (DP = ISIT or ISDT), the more accurate forecasting model usually produced lower total costs for the supplier, retailers and the entire supply chain under lower EOC. When EOC became larger, however, more accurate forecasting models (ACT and WIN) could produce higher TC than a less accurate forecasting model. For example, when EOC = 8 and DP = ISDT, the naive model (FM = NAV) and the simple moving average model (FM = SMA) resulted in the lower total cost for the manufacturer, retailers and the entire supply chain than the ACT and WIN models. The reason for this is that when NAV or SMA was used for demand with decreasing trend, there was a positive bias for the forecast (i.e. the forecast usually exceeds the demand). When the retailers placed orders in advance to the manufacturer, the manufacturer improved its capacity utilization, thus NAV and SMA performed better than ACT and WIN. The result revealed that selecting the proper forecasting model in combination with the proper level of early order commitment could significantly improve the performance of the supply chain with cost savings of up to 30 to 50%. Therefore, the findings supported Hypothesis 3 of this study.

6.3. *Interaction among EOC, capacity tightness and forecasting model*

Referring back to the ANOVA results in table 2, the three-way interaction CT $\times$ FM $\times$ EOC had significant effects (p-values < 0.0001) on all performance measures except TCM. To examine the impact of capacity tightness on the performance of forecasting models and values of early order commitment, the performances of different EOCs using different forecasting models were investigated for CT = low, medium and high, respectively. The important result is summarized here and detailed statistical analyses are available from the authors upon request.

Our analyses showed that, when CT = low, a larger EOC value would result in a lower total cost and a higher service level for the manufacturer (TCM and SLM), but a higher total cost for the retailers (TCR). When the forecast was perfect (FM = ACT), a larger EOC value resulted in a higher service level for the retailers (SLR); however, when the forecasts were not perfect, it could possibly result in a lower service level for retailers. The total cost for the entire supply chain usually first decreased and then increased as EOC increased. The improvement in the performance of the manufacturer was a result of better capacity utilization when earlier orders were received. The manufacturer's better capacity utilization would positively influence the retailers' service level. Only when the capacity tightness and the forecasting accuracy were both low did the negative effect outweigh the positive effect of early order commitment, resulting in an increase of the back order costs for the retailers.

When the capacity tightness was medium or high, a larger EOC would produce lower total costs for the manufacturer (TCM), the retailers (TCR), and the entire supply chain (TC). Earlier placement of orders by the retailers could help the manufacturer improve its capacity utilization, which, in turn, helped reduce backorder costs for both the manufacturer and the retailers when the manufacturer's capacity would become tight due to no early order commitment. Early order commitment could lead to the greatest cost savings when the capacity tightness was at the medium level. The total cost savings of placing orders 8 days earlier ranged from 70% to 107% depending on the forecasting model used when the capacity tightness was at the medium level. When the capacity tightness was at the low level, the corresponding cost savings were less than 17%.

The magnitudes of cost savings of early order commitment varied significantly depending on the different combinations of capacity tightness and the forecasting model. When CT = medium and FM = NAV, an EOC of 8 could produce over 100% cost savings compared to an EOC of 0. Using the same forecasting model, the corresponding cost saving was only 42% when CT = high. The reason for the lower cost savings is that when the capacity was very tight, the manufacturer already had to use most of its capacity to produce, even without any early order commitment. Therefore, there was less room for improving capacity utilization even if the retailers placed their orders earlier.

Overall, the simulation results showed that capacity tightness was a significant factor determining the effectiveness of different EOC values and forecasting models, thus supporting Hypothesis 4 of this study.

7. Managerial Implications

In this paper we studied the relationships among forecasting models, early order commitment, capacity tightness and the performance of a supply chain consisting of one manufacturer and four retailers. Through comprehensive simulation experiments and subsequent analyses of the simulation results, we were able to discern the effectiveness of early order commitment and forecasting models under different scenarios. To facilitate the discussions that would be useful to management, the results based on Duncan's multiple range tests at the 5% significance level for all simulated scenarios were summarized and presented in table 4. The symbols + and

Forecasting models	Model parameters	Performance measures				
		TC	TCM	TCR	SLM	SLR
ACT	DP = ICON	(+)	+	(–)	+	(+)
	DP = ISEA	(+)	+	(–)	+	(+)
	DP = ISIT	+	+	+	+	(+)
	DP = ISDT	(+)	(+)	(+)	+	(+)
	DP = MIX	(+)	+	(–)	+	(+)
	CT = LOW	(+)	(+)	(–)	(+)	(+)
	CT = MED	(+)	+	+	+	(+)
	CT = HIGH	+	+	+	+	+
NAV	DP = ICON		+	–	+	–
	DP = ISEA		+	–	+	
	DP = ISIT	+	+	+	+	
	DP = ISDT	+	+	+	+	
	DP = MIX		+	–	+	
	CT = LOW		(+)	–	+	
	CT = MED	+	+	+	+	
	CT = HIGH	+	+	+	+	
SMA	DP = ICON	(+)	+	–	+	–
	DP = ISEA		+		+	
	DP = ISIT	(+)	+	(+)	+	
	DP = ISDT	+	+	+	+	
	DP = MIX		+	–	+	(–)
	CT = LOW		(+)	(–)	+	
	CT = MED	+	+	+	+	
	CT = HIGH	+	+	+	+	
WIN	DP = ICON	(+)	+	(–)	+	–
	DP = ISEA	(+)	+	(–)	+	–
	DP = ISIT	(+)	(+)	(+)	(+)	
	DP = ISDT	(+)	+	+	+	(+)
	DP = MIX	(+)	+	(–)	+	–
	CT = LOW		(+)	(–)	+	–
	CT = MED	+	+	+	+	
	CT = HIGH	+	+	+	+	

The symbols in the table indicate the impact of increasing EOC on the five performance measures under different combinations of forecasting model (FM), demand pattern (DP) and capacity tightness (CT). The symbol + (or –) are used to indicate that an increase of EOC would have a significantly positive (or negative) effect on the performance measure (i.e. the Duncan's ranking results were either in ascending or descending order with no tie as the value of EOC increased from 0 to 8). The symbol (+) or (–) indicate that there was a general, but not definitive, pattern of positive or negative effect (i.e. although an increase of EOC would have a positive or negative effect on the performance measure, but there were ties in the rankings). The blank space indicates that there was no clear increasing or decreasing pattern as EOC increased.

Table 4. The impact of increasing EOC values on performance measures.

– were used for those scenarios in which a clear pattern of significantly positive or negative effect on performance measures was identified (i.e. the ranked results were either in ascending or descending order with no tie) as the value of EOC increased from 0 to 8. When only a general, but not definitive, pattern of positive or negative effect was found (e.g. due to a tie of ranks), a symbol of (+) or (–) would be used.

7.1. *Selection of early order commitment periods*

Table 4 clearly shows that the manufacturer would benefit most in terms of cost reduction and service level improvement when retailers made early order commitments. With an extended planning horizon as a result of early order commitment from the retailers, the manufacturer could better realize trade-offs between set-up cost and inventory carrying cost with the capacitated lot-sizing procedure, thus significantly reducing its total cost. However, early order commitment worked against the retailers for all demand patterns except those cases with increasing or decreasing trends of demand. The inventory carrying cost would increase significantly for the retailers when they had to place orders more days in advance with a less accurate demand forecast. The result indicated that a proper level of EOC should be selected to balance the cost savings of better resource utilization (for the manufacturer) and the cost increase of higher forecasting errors and inventory cost (for the retailers).

Benefits to the retailers were even less obvious in terms of improving the service level performance. While early order commitment could help improve the service level for the manufacturer in a consistent manner, it actually reduced the service level for retailers in many cases, unless the retailers knew the demand with certainty in advance. Since it is rare for the retailers to forecast the demand with such accuracy, the manufacturer might need to provide some incentives or a cost-sharing plan to the retailers to effectively implement the early order commitments.

From table 4, we also found that capacity tightness significantly influenced the cost savings that could be achieved through early order commitment. Only when the capacity tightness was either at the medium or high level, would early order commitment provide mutual benefits to both the manufacturer and the retailers. Early order commitment worked best when the capacity tightness was at the medium level. When the capacity is tight, the total cost savings from early order commitment was less obvious. This is because the manufacturer had already used most of its capacity to produce, even without any early order commitment, when the capacity is tight. Therefore, there was less room for improving capacity utilization even if the retailers placed their orders earlier.

7.2. *Choice of forecasting models*

Our findings showed that the choice of forecasting model alone did not account for the cost savings achieved. The effectiveness of early order commitment in conjunction with different forecasting models was largely determined by the accuracy of the models' demand forecast. When the retailers used a simple naive model (which had the largest forecasting error in our simulation) to forecast demand, everyone in the supply chain could achieve the highest total cost savings through early order commitment given that all retailers faced identical demands with trends or when the capacity tightness was medium or high. If the forecast was already quite accurate to begin with, and the total cost was relatively low with no early order commitment, the potential of further reducing the total cost was small. The result suggested that choosing a forecasting model with the minimum forecasting error might not necessarily yield the best result. A simple forecasting model with proper early order commitment could yield a lower total cost than merely selecting the most accurate forecasting model.

The effectiveness of forecasting models also depended on the demand patterns in our simulation. Our results suggested that demand patterns significantly influenced the cost savings that could be achieved through early order commitment. Early order commitment could provide more cost reduction for the retailers, the manufacturer, and the entire supply chain when the retailers faced identical demand with trends, either increasing or decreasing. However, if the demand patterns had only random or seasonal fluctuation, placing orders earlier would only benefit the manufacturer but not the retailers. The total cost of the supply chain would depend on the trade-off between the cost savings of the manufacturer and the extra cost of the retailers. Given a random or seasonal demand pattern, the total demand of the supply chain was rather smooth over the time horizon and the desired output is often below the manufacturer's capacity most of the time. As a result, the retailers' service level was quite high, as they would receive their orders on time. Inevitably, the inventory carrying cost for the retailers would increase significantly because of the higher manufacturer's service level and lower forecasting accuracy.

The impacts of the forecasting models on the effectiveness of early order commitment were quite different depending on the various levels of capacity tightness. More cost savings could be achieved when the capacity tightness was at the medium level and the manufacturer had more options to utilize the resource for an extended production planning horizon. When the capacity tightness was low, more accurate forecasting models usually performed better for any specific EOC values. However, if the forecasting accuracy was low, the negative effect would outweigh the positive effect of early order commitment, resulting in an increase of the back order costs (and the total costs) for the retailer.

8. Conclusions

By simulating inventory replenishment decisions by retailers and production/ distribution decisions by the manufacturer, this study provides more insights into the value of early order commitment between the manufacturer and the retailers experiencing demand uncertainty. The findings have important implications for management to balance the needs of selecting the proper forecasting models and the extent of early order commitment in managing supply chain activities. Among the most important findings of this study are the following.

- A relatively large value of EOC is beneficial to both the manufacturer and retailers in terms of cost reduction when the demand pattern is increasing or decreasing or when the capacity tightness is medium or high.
- A relatively large value of EOC is beneficial to the manufacturer but detrimental to the retailers in terms of cost reduction when the demand pattern is mixed or seasonal or when the capacity tightness is low.
- The choice of forecasting models is less important than the choice of EOC values in determining the benefits for the members in the supply chain. However, a proper forecasting model will enhance the effectiveness of early order commitment.

8.1. *Heuristics for managerial decision-making*

While early order commitment allows the manufacturer to plan ahead and better use its capacity to reduce costs and improve service levels for the supply chain, this study shows that its benefits and effectiveness could be affected by the prevailing demand patterns, available capacity, and the corresponding forecasting methods used. Findings from this study provide numerous managerial insights concerning the interaction between the choice of forecasting models and early order commitment. Without sifting through massive data analyses, managers would greatly benefit from developing a set of heuristics for making quicker and better decisions on the use of early order commitment. The following is a sample of simple heuristics aimed at minimizing the total cost of a supply chain that can be used in combination with any forecasting model (excluding ACT which has no forecasting error and is not practical in real life situations).

- For demand patterns with increasing or decreasing trend, use a relatively long early order commitment (optimal EOC = 8 in this simulation study).
- For demand patterns with seasonal fluctuation but no trend, use a moderate early order commitment (optimal EOC = 6).
- For constant or mixed demand patterns, use a moderate early order commitment (optimal EOC = 4).
- For production systems with a medium or high capacity tightness, use a relatively long early order commitment (optimal EOC = 8).
- For production systems with a low capacity tightness, use a moderate early order commitment (optimal EOC = 4 and 6).

8.2. *Limitations and future research directions*

This simulation study has several inherited limitations that can present future research opportunities. Firstly, the supply chain simulated in this study is only a simplified case with only one capacitated manufacturer and four retailers dedicated to only a single product. It will be useful to examine the impact of supply chain configurations on the key conclusions of this study.

Secondly, we have only examined one method of ordering coordination: retailers place orders earlier. There are many other alternative methods of coordinating orders in practice, such as Vendor Managed Inventory (VMI) or Continuous Replenishment Programs (CRP), to name a few. Future studies should evaluate the performance of these alternative methods.

Thirdly, the cost data (ordering or set-up cost, transportation cost, inventory carrying or backorder cost) used in this study only represents one special case. A different cost structure may have a significant impact on the performance of forecasting models and the value of early order commitment.

Fourthly, this study assumes that the manufacturer has the same type of relationship with the retailers and thus does not give preferred treatment to any retailers. In reality, the relationship intensity or preference would be a key issue as the number of retailers increased. How this relationship differentiation affects the production and distribution decision should also deserve further investigation.

Finally, we assume the manufacturer uses a capacitated lot-sizing rule to make its production decision and retailers use EOQ to make their inventory decisions in this study. Both the manufacturer and the retailers could have used many other heuristic rules in making such decisions. How these alternative production and inventory policies will influence the value of early order commitment should be of concern to the practitioners as well as academicians.

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