Assessing the value of early order commitment for supply chains with (s, S) policies and lost sales

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Abstract: Early order commitment (EOC) is one of the strategies for supply chain coordination, wherein a retailer places its orders to a supplier in advance, i.e., the retailer's ordering lead time is longer than the regular delivery time from the supplier to the retailer. This paper explores the value of practicing EOC in a supply chain with demand uncertainty and lost sales. It also examines the impact of forecasting errors and inventory policies used by the retailers on the performance of the supply chain. The methodology adopted in this study is computer simulation. Analyses of the simulation outputs show that:

1 using the periodical review (s, S) policy can reduce the cost of the supply chain in many environments compared to deterministic lot-sizing rules such as the economic order quantity rule, the periodic order quantity rule and the Silver-Meal rule
2 the EOC strategy can generate significant cost savings for the whole supply chain when the retailers' forecasting errors are not too large or the supplier's forecasting horizon is relatively long.

However, the advantage of EOC disappears when the forecasting errors are large and the supplier's forecasting horizon is very short. Sensitivity analyses show that these findings are robust with respect to the supply chain's cost structure and the supplier's production lead time.

Keywords: supply chain simulation; early order commitment; EOC; inventory policy; (s, S) policy; lost sales; forecasting error.

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1 Introduction

The coordination of separate functional activities such as raw material purchasing, production and inventory control, distribution and logistics, etc., is one of the most important and valuable tasks in supply chain management. Previous research discovered that the coordinated decisions of the whole system across a wide spectrum of business organisations and geographical locations can effectively reduce the total cost and improve the service level of the supply chain. In practice, much business focused their attention on finding a centralised decision not only in the entrails of the enterprise, but also among the supply chain, in order to reduce costs and serve their customers better. Many factors are considered to arrive at a better decision, among which inventory policy (IP), early order commitment (EOC) and information sharing are proved to be impactful and practicable (Ferguson and Ketzenberg, 2006; Lee et al., 1997; Lau et al., 2008; Huang et al., 2003). In particular, information technology (IT) has made possible real-time, online communications among all constituencies within a supply chain and become supply chain 'enablers' that can substantially improve information transparency and reduce lead times and non-value-added activities (Handfield and Nichols, 1999). On the other side, although many findings from academic researches can be used in business with the help of IT, how to choose a befitting one in practice is still a problem.

The purpose of this study is to set up an experimental model that simulates a decentralised supply chain and explores the interactions among forecasting errors, inventory policies and EOC strategies. EOC is one of the strategies for supply chain coordination, wherein a retailer places its orders to a supplier in advance, i.e., the retailer's ordering lead time is longer than the regular delivery time from the supplier to the retailer (Zhao et al., 2001). Obviously, EOC helps the manufacturer to make wise production and inventory decision and alleviates the negative influence caused by demand uncertainty. However, EOC increases the risk of the retailers, who have to forecast much earlier and take more consequences caused by misestimating the demand. Therefore, an incentive scheme must be provided by the supplier to induce the retailers to practice EOC. Gilbert and Ballou (1999) conducted an analysis of a steel distribution supply chain and quantified the maximum discount that can be offered to consumers who commit to orders in advance. Cvsa and Gilbert (2002) examined the trade-off between EOC and order postponement in the context of competition. Tang et al. (2004) and McCardle et al. (2004) investigated the benefits of advance booking discount programme with or without retail competition. Zhao et al. (2007) and Xie et al. (2010) developed an analytical model to quantify the cost savings of EOC in a two-level supply chain where demand is serially correlated. Their results showed that EOC could experience greater savings when:

a the inventory item received less value-added activities at the retailer site

b the manufacturing lead time was short

c demand correlation over time was positive, but weak

d the delivery lead time was long.

The most relevant works to the current research are Zhao et al. (2001, 2002) and Lau et al. (2008), where they built computer simulation models to conduct extensive researches on the effects of EOC in two-level supply chains consist of a single capacitated supplier and multiple retailers. They found that the benefits of EOC could be influenced by a combination of demand patterns (DPs) faced by the retailers, forecasting models and inventory policies adopted by the retailers, and the production capacity tightness of the supplier. These researches provide a much clearer picture than the analytical models about the effects of EOC in real world supply chain management. However, after carefully checking their simulation models, the following disadvantages appear:

1 All the inventory policies used by the retailers in their studies are all belong to the deterministic lot-sizing rules, such as the economic order quantity (EOQ) rule, the periodic order quantity (POQ) rule, the Silver-Meal (SM) lot-sizing rule (Silver and Meal, 1973) and the part-period balancing rule (Berry, 1972). However, since the market demands faced by the retailers are stochastic, the use of these deterministic lot-sizing rules is suspicious and it is unknown that whether the findings from their researches are still valid when the decision-makers choose to use some stochastic inventory policies. For example, in many single-item inventory systems, it is well-known that an optimal policy exists within the class of periodical review (s, S) policy (Zheng and Federgruen, 1991), where s and S refer to the reorder point and the order-up-to level respectively. Therefore, it is meaningful to develop a simulation model to investigate the impact of (s, S) policy on the value of EOC.

2 The supplier in their studies, which is a capacitated manufacturer, uses also a deterministic (and capacitated) lot-sizing rule developed by Chung and Lin (1988) to make production decisions. In practice, another type of two-level supply chains might be more popular, in which the supplier is a wholesaler who purchases merchandise from an upstream manufacturer who manufactures several products subject to production lead times. The wholesaler is not restricted by their own capacity when they purchase goods from its upstream manufacturer, but a positive purchasing lead time does exist. In this case, it is more practical to assume that the wholesaler also uses a periodical review (s, S) policy to control its inventory.

3 All the shortages are backordered in their studies. However, for many common products, when the retailers stock out, it is most possible that the sales are lost, since the customers can usually look for substitutes elsewhere. For most business, the penalty cost for lost sales is more expensive than that of the backorders.

This research is motivated by examining whether previous findings concerning the value of EOC still hold under more realistic situations. We assume the supply chain consists of a supplier (it can be considered as either a wholesaler or a manufacturer) that supplies a single product to several retailers at different distance. Each of the retailers makes their inventory decision independently by using some inventory policies based on their own demand forecast. The supplier elaborates products or bulks purchase from its upstream supplier using periodical review (s, S) policy subject to a positive lead time. Unfilled demand will become lost sales.

In this research, four inventory policies are considered for the retailers: the EOQ rule, the POQ rule, the SM rule and the periodical review (s, S) policy (SS). The retailers can commit their purchasing orders in advance, which are fixed both in quantity and delivery time, earlier than a planned lead time to the suppliers. The focus of the research is to analyse the impact of forecasting errors, inventory policies, and EOC on the performance of the supply chain and investigate their interrelationships in a variety of business environments. The performance of the supply chain is depicted by the total cost of the supply chain, the cost of the supplier and the cost of the retailers.

Many operational factors which may affect the decisions along the supply chain are considered in our model, including DPs, cost structures, supplier's production or purchasing lead time, etc. Specifically, we will do the followings:

1 compare the performance of (s, S) policy with those of the deterministic lot-sizing rules

2 investigate the effects of the EOC strategy under a variant of forecasting errors, when both the supplier and retailers use the periodical review (s, S) policy to control their inventories

3 examine how robust are the findings from the study under different operational settings such as the supply chain's cost structure and the supplier's purchasing lead time.

The paper is organised as follows. The next section presents the details for the supply chain environment which is considered in this research. Then, the experimental design for the simulation is followed. Subsequently, the results of the statistical analyses on the data generated from the simulation are presented. Finally, managerial implications and conclusions are summarised.

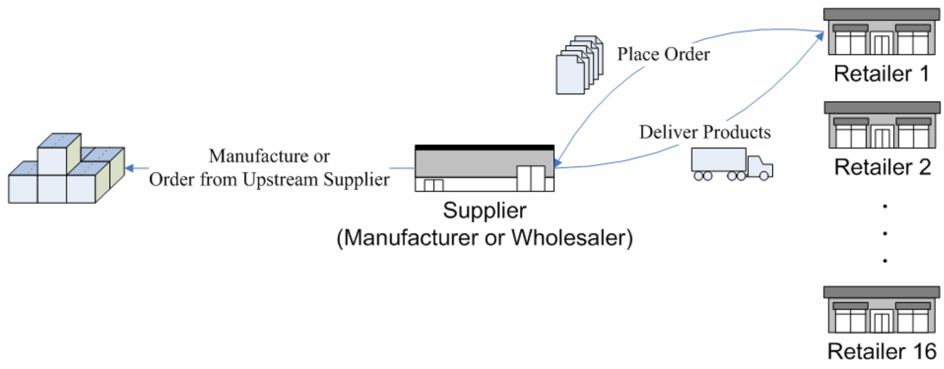
2 The supply chain environment

2.1 Basic assumptions

A simulation model involving a simple, two-stage supply chain was constructed, in which a single supplier sells a single product for 16 retailers (Figure 1). This model was modified from the models used by Zhao et al. (2001, 2002) and Lau et al. (2008). The supplier is a manufacturer who manufactures a product with respect to a fixed production lead time (alternatively, the supplier can be a wholesaler who purchases goods from its upstream manufacturer subject to a positive purchasing lead time). When orders from the retailers arrived, the supplier calculates its inventory position and uses a periodical review (s, S) policy to schedule its production (or purchasing) plan.

Only the retailers face customer demands and the average demand for each retailer is 1,000 units per period. The retailers use EOC strategy to purchase products from the supplier with the help of certain inventory policies.

Figure 1 The supply chain (see online version for colours)



In our simulation, three levels of production lead time (PT) are designed for the supplier. They are set at four, eight and 16 periods respectively. Nine levels of EOC periods are considered and they are expressed as the ratio to PT, which are zero, 1/8, 1/4, 3/8, 1/2, 5/8, 3/4, 7/8 and one respectively. We use EOCT to stand for the number of EOC periods, i.e., EOCT = PT × EOC. Obviously, if EOC = 1, then EOCT equals to PT, thus, it is unnecessary for the supplier to make any forecast when make its production decisions, since the future demands (the deliveries requested by the retailers) for the supplier within the production lead time are all known.

The supplier delivers products to the retailers by truck and we assume the truckload is sufficiently large (or the products are relatively small in volume), thus, a shipment to any retailer could be completed by a single truck. The delivery lead time (DT) from the supplier to each retailer is assumed to be two periods.

Figure 2 describes the order and delivery flow in the simulation. Assume a retailer places one order in period t (current time). The supplier receives the order information immediately and should fulfil the order in period t + EOCT (the retailer will receive the shipment in period t + EOCT + DT). In current period t, after calculating its on-hand inventory and the net requirement in the future, the supplier makes its production plan using periodical review (s, S) policy. In period t + PT, the production setup in period t will complete and the products will come into the stock of the supplier.

Figure 2 An order and delivery flow in the simulation (see online version for colours)

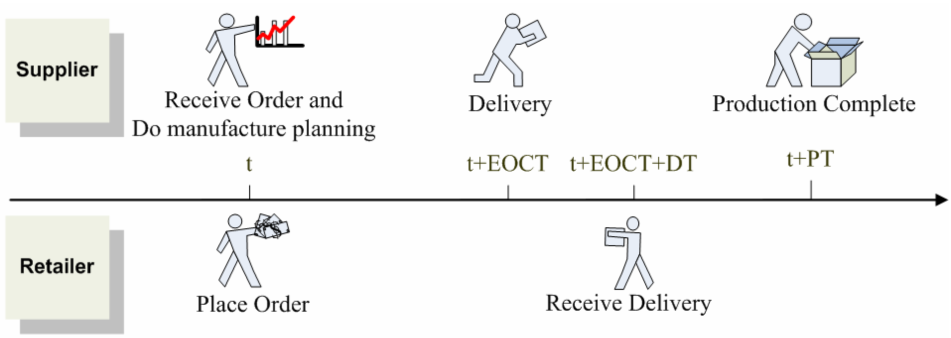


Table 1 Cost structures

Supplier/retailer	*Supplier*	*Type-1 retailer*	*Type-2 retailer*	*Type-3 retailer*	*Type-4 retailer*
Case A (base): low inventory carrying cost, low shortage penalty					
Order processing cost ($/order) (Transportation cost excluded)	2,000.00 (Setup cost)	30.00	30.00	30.00	30.00
Transportation cost ($/truck)	N/A	450.00	255.00	331.00	553.00
Holding cost ($/unit/period)	0.015	0.02	0.02	0.02	0.02
Backorder cost ($/unit/period)	0.30	-	-	-	-
Shortage penalty ($/unit) (Opportunity cost)	-	3.00	3.00	3.00	3.00
Case B: low inventory carrying cost, high shortage penalty					
Order processing cost ($/order) (Transportation cost excluded)	2,000.00 (Setup cost)	30.00	30.00	30.00	30.00
Transportation cost ($/truck)	N/A	450.00	255.00	331.00	553.00
Holding cost ($/unit/period)	0.015	0.02	0.02	0.02	0.02
Backorder cost ($/unit/period)	1.50	-	-	-	-
Shortage penalty ($/unit) (Opportunity cost)	-	6.00	6.00	6.00	6.00
Case C: high inventory carrying cost, low shortage penalty					
Order processing cost ($/order) (Transportation cost excluded)	2,000.00 (Setup cost)	30.00	30.00	30.00	30.00
Transportation cost ($/truck)	N/A	450.00	255.00	331.00	553.00
Holding cost ($/unit/period)	0.03	0.04	0.04	0.04	0.04
Backorder cost ($/unit/period)	0.30	-	-	-	-
Shortage penalty ($/unit) (Opportunity cost)	-	3.00	3.00	3.00	3.00
Case D: high inventory carrying cost, high shortage penalty					
Order processing cost ($/order) (Transportation cost excluded)	2,000.00 (Setup cost)	30.00	30.00	30.00	30.00
Transportation cost ($/truck)	N/A	450.00	255.00	331.00	553.00
Holding cost ($/unit/period)	0.03	0.04	0.04	0.04	0.04
Backorder cost ($/unit/period)	1.50	-	-	-	-
Shortage penalty ($/unit) (Opportunity cost)	-	6.00	6.00	6.00	6.00

Table 1 summarises the cost structures used in this study which are modified from Zhao et al. (2001), where their cost structure design mimicked one of their case studies. Specifically, among the 16 retailers, four of them are assumed to be Type-i retailers, for each i = 1, 2, 3, 4. For Type-i retailers, the transportation costs are $450, $255, $331 and $553 for i = 1, 2, 3, 4 respectively. When a retailer places an order to the supplier, a fixed order processing cost of \$30 is incurred. So, the actual order cost for the retailers is the sum of transportation cost and order processing cost. The supplier should pay \$2,000 to start up a new production, which includes the opportunity cost for the production setup time and any other cost for setting up the production run. Another category of cost for the supplier and retailers is the inventory carrying cost. The cost includes the rental and operation of warehouse space and the opportunity cost of the capital. When the products are out of stock in the supplier's site, the supplier should pay backorder cost to the retailers; and when the products are out of stock in the retailer's site, demands that cannot be fulfilled lose immediately and we consider the opportunity cost (product profits) as the shortage penalty for the retailer. Finally, four different cost structures (Cases A, B, C, D) are considered by varying the inventory carrying cost and shortage expense (backorder cost for the supplier and opportunity cost expenses for the retailers).

The length of the simulation run is set to be 410 periods. The first 50 periods are used to warm up the simulation, including the demand forecasts and order decisions made by the supplier and retailers. The first 50 periods and last ten periods are excluded from the performance measures calculations in order to analyse the simulation data in steady-running status. Therefore, the final performance measures are bases on 350 periods, which is almost a year if one period stands for just one day.

In order to avoid possible stock shortage during the first few periods, sufficient initial inventories are assumed for the supplier and retailers. In our simulation, the supplier has an initial inventory of 160,000 units and the retailer's initial inventory is set to be 10,000 + 1,000 * r (for retailer $r = 1, 2, \dots, 16$). We set them unequal in order to prevent all retailers placing their first orders at the same period.

The simulation procedure consists of three phases to be discussed below.

2.2 Phase I: generating randomised demand

The first phase of the simulation generates demands for all the retailers. In particular, demand for each retailer is generated by a corresponding demand generator given by Zhao et al. (2001, 2002):

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

where

$demand_t$ is the demand in period t ($t = 1, 2, \dots, 410$)

snormal() is a standard normal random number generator

SeasonCycle = 7 for demand varying weekly.

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 is approximately 1,000 units. Since there is a normal variate in the demand generator function, the demand generated may take a negative value. We eliminate the possibility by restricting the value produced by the standard normal random number generator to between –3.0 and +3.0.

Eight DPs are used in our research. Table 2 lists their characteristic parameters, which represent variety of consumer demands.

Table 2 Demand patterns

#	*DP*	*Base*	*Slope*	*Season*	*Noise*
1	LIS	775.5	1	100	50
2	HIS	551.0	2	200	100
3	LDS	1,224.5	–1	100	50
4	HDS	1,449.0	–2	200	100
5	LCS	1,000.0	0	100	50
6	HCS	1,000.0	0	200	100
7	LC	1,000.0	0	0	50
8	HC	1,000.0	0	0	100

Notes: L – low variability, H – high variability, I – increasing trend, D – decreasing trend, C – constant (no trend) and S – seasonality. For example, HIS means the DP of high variability with increasing trend and seasonal fluctuation; and LC means the DP of low variability with neither trend nor seasonal fluctuation.

2.3 Phase II: retailers' ordering decisions

For all the retailers, the planning horizon of the replenishment plan is 32 periods, which is twice of the maximum possible PT (16 periods) and the replanning periodicity is set to one period. In reality, plenty of forecasting models can be used by retailers to forecast intending demands during the planning horizon, based on which they decide when and how many units to order form the supplier. In this study, adopting the ideas from Zhao et al. (2002), forecasting errors are investigated instead of certain forecasting models and they are assumed to be normally distributed and characterised by two parameters: forecast error bias (EB) and forecast error deviation (ED). Specifically, the demand forecast made at period t_0 for period t ($t > t_0$) is generated according to the following formula (Zhao et al., 2002):

$$forecast_t = demand_t \times \{1 + EB + ED \times [1 + (t - t_0) / 4.85] \times snormal()\},$$

where $demand_t$ is the actual demand in period t (t = 1, 2, … , 410) and *snormal*() is a standard normal random number generator. We investigate four EB levels which are –5%, zero, 5% and 10%, and four ED levels which are zero, 5%, 10% and 20%.

Four types of inventory policies are considered in our experiment: EOQ, POQ, SM and SS policy. So, the retailer has to calculate the net requirement for the remaining (32 – EOCT) periods, where EOCT refers to the number of EOC periods. The retailer fulfils the customers' demands by on-hand inventory and demands unfilled on time get lost if the products are out of stock.

2.4 Phase III: supplier's production and delivery decision

In each period, the supplier receives current period's orders from retailers and uses the simple moving average forecasting method to predict demands in the next PT periods, where PT refers to the production lead time for the supplier. The only parameter required for the simple moving average forecasting method is the number of past periods used to average the demand and this is determined by minimising the mean absolute deviation

(MAD) of the forecasting errors over the previous 50 periods. Then the supplier uses the periodical review (s, S) policy (Zheng and Federgruen, 1991) to make decision on its production planning schedule.

At the end of each period, and after the production started PT periods before (if there is any) finished, the supplier makes its shipping decisions. If on-hand inventory is sufficient, he fulfils retailers' orders (plus backorders if there are any) placed by the retailers EOCT periods before; 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 shortages become backorders. The shipment will arrive at retailers DT periods later, which is the transportation lead time from the suppliers to retailers.

The process is repeated until all ordering, production and delivery decisions have been developed for all 410 periods. After the entire simulation is completed, we calculate all cost items for the supplier and retailers. The total cost (including setup, order processing, transportation, holding and shortage penalty cost) will be used to measure the performance of the supply chain. As indicated earlier, all measures are only calculated with the data from periods 51 to 400.

3 Experimental design

3.1 Independent variables

There are seven independent variables in the experiment and they are grouped into three categories: environmental factors, forecasting error parameters and decision variables. Since they have been explained in details in last section, here, we just summarise them in Table 3.

Table 3 Independent variables in the simulation experiment

Category	*Factor name*	*Label*	*Levels*	*Values*
Environmental factors	Cost structure	CS	4	Cases A, B, C, D
	Supplier's production lead time	PT	3	4, 8, 16 periods
	Demand pattern	DP	8	LIS, HIS, LDS, HDS, LCS, HCS, LC, HC
Forecast error parameters	Error bias	EB	4	–5, 0, 5, 10 (%)
	Error deviation	ED	4	0, 5, 10, 20 (%)
Decision variables	Inventory policy	IP	4	EOQ, POQ, SM, SS
	Early order commitment	EOC	9	0, 1/8, 1/4, 3/8, 1/2, 5/8, 3/4, 7/8, 1

3.2 Performance measures

We use total cost to measure the performance of the supply chain and three types of measure criteria are used in the study which are defined as follows:

- total cost for the retailers (TCR): sum of the ordering processing cost, transportation cost, inventory carrying cost and shortage penalty of all retailers

- total cost for the supplier (TCS): sum of the setup cost, transportation cost (only for backorders deliveries), inventory carrying cost and backorder cost
- total cost for the entire supply chain (TC): sum of the TCR and TCS, but minus backorder cost paid by the supplier to the retailers (as it is only an internal cost within the entire supply chain).

4 Results and analyses

4.1 Basic ANOVA and Duncan's grouping results

For each combination of the seven independent variables (CS, PT, DP, EB, ED, IP, EOC), five simulation runs are conducted to reduce the random effects. The simulation results are presented in two steps: the base case (Subsections 4.1–4.4) and the sensitivity analyses (Subsection 4.5). For the base case, we fixed CS to Case A (as shown in Table 1) and PT = 8 periods. For the sensitivity analyses, we examine the robustness of the findings from the base case when CS and PT changes.

The simulation output for the base case is first analysed using the SAS analyses of variance (ANOVA) procedure. Table 4 presents selected ANOVA results. A primary finding from this research is that DP does not significantly impact the performance of the supply chain, which completely differs from previous findings in Zhao et al. (2001, 2002). For supply chains with a capacitated supplier and backorders, where deterministic inventory policies are adopted, they showed that DP does significantly influence the performance of the supply chain. However, for supply chains with (s, S) inventory policies and lost sales, this study shows that DP is no longer a crucial factor to be considered. Therefore, in the rest of the paper, we drop off the discussions on DP.

Table 4 Selected ANOVA results for significant effects

Source	*TC**		*TCS***		*TCR****	
	F-value	*Pr > F*	*F-value*	*Pr > F*	*F-value*	*Pr > F*
EB	37,088.2	<.0001	440.9	<.0001	37,838.1	<.0001
ED	67,455.8	<.0001	136.35	<.0001	72,470.5	<.0001
EOC	4,406.85	<.0001	24,973.1	<.0001	8,744.18	<.0001
IP	9,468.14	<.0001	5,574.6	<.0001	3,944.05	<.0001
EB * ED	5,615.17	<.0001	10.19	<.0001	5,812.26	<.0001
EB * EOC	1,383.13	<.0001	16.48	<.0001	1,142.37	<.0001
EB * IP	2,113.79	<.0001	25.38	<.0001	2,144.7	<.0001
ED * EOC	868.59	<.0001	94.36	<.0001	710.13	<.0001
ED * IP	1,349.7	<.0001	1,251.98	<.0001	1,886.65	<.0001
IP * EOC	172.6	<.0001	248.82	<.0001	92.49	<.0001

Notes: *Based on residual analyses and the suggestion by SAS, inverse square transformation of TC (i.e., TC^{-2}) is made to satisfy the assumptions of ANOVA.
**Based on residual analyses and the suggestion by SAS, inverse square transformation of TCS (i.e., TCS^{-2}) is made to satisfy the assumptions of ANOVA.
***Based on residual analyses and the suggestion by SAS, TCR is raised to the power of –1.5 (i.e., $TCR^{-1.5}$) to satisfy the assumptions of ANOVA.

The simulation output for the base case is also analysed using the Duncan's (1955) multiple range tests. Table 5 lists the Duncan's grouping on main effects. The effects of the forecasting errors (EB and ED), IP and EOC will be examined in detail in Subsections 4.2–4.4.

Table 5 Duncan's grouping on main effects

Dependent variables		*TC*	*TCS*	*TCR*
Source		*Rank*	*Rank*	*Rank*
EB	–5	4	1	4
	0	2	2	2
	5	1	3	1
	10	3	4	3
ED	0	1	1	1
	5	2	2–3	2
	10	3	2–3	3
	20	4	4	4
IP	EOQ	3	1–2	3
	POQ	2	1–2	2
	SM	4	4	4
	SS	1	3	1
EOC	0	3	6–8	1
	1/8	1	4	2
	1/4	2	2	3
	3/8	4	5	4
	1/2	5–6	6–8	5
	5/8	7	9	6
	3/4	8	6–8	7
	7/8	9	3	8
	1	5–6	1	9

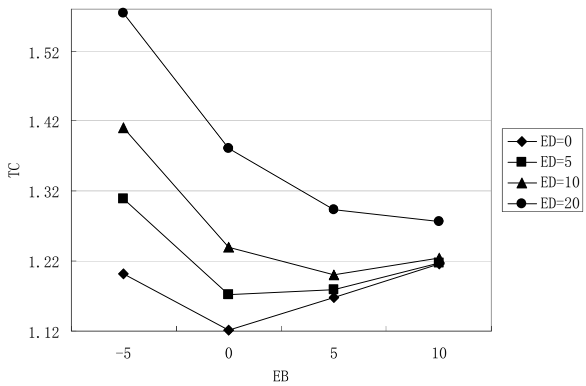
4.2 Impact of the components of forecasting errors

The ANOVA results in Table 4 show that the effects of both EB and ED are significant in terms of TC and TCR. In particular, ED has the largest F-value than EB and other factors. Duncan's groupings in Table 5 show that TC, TCS and TCR all increase as ED increases from zero to 20%, i.e., a higher ED always results in a higher cost for the supplier, the retailers and the entire supply chain.

The impact of EB on TC, TCS and TCR is somewhat different. Generally speaking, a moderate value of EB (EB = 5%) leads to the lowest TC and TCR, but not the lowest TCS. If EB has a negative value (EB = –5%), the supply chain has the worst performance and the retailers have to pay for the highest cost.

Figure 3 plots TC under various combinations of EB and ED. Consistent with one's intuition, lowest TC occurs under the perfect forecast (EB = 0 and ED = 0). As ED increases from zero to 20%, the value of EB that minimises TC gradually increases from zero to 10%. Since the supply chain is a system with lost sales, shortage penalties to the retailers are much higher than that to the supplier. Furthermore, when retailers are out of stock, unfilled demands lose immediately but products they ordered from the supplier cannot be cancelled. When the ordered products arrive, retailers cannot sell them out until the next few periods. Thus, a stockout at a retailer's side results in not only a higher shortage penalty cost, but also a higher inventory carrying cost for the retailer. When ED > 0, moderately overrating the demands can act as a part of safety stock for the retailers, thus, reduces the cost for the retailers and the entire supply chain. A higher ED always requests a larger safety stock, and thus, a larger value of EB can lead to a better supply chain performance.

Figure 3 Interactive effects of EB and ED on TC



4.3 Impact of retailers' inventory policies

The ANOVA results in Table 4 indicate that retailers' IP is one of the most significant factors in the experiment. The selection of inventory policies is significant in influencing total cost for both the supplier and the retailers and the interaction between IP and forecasting errors (EB and ED) also significantly affects all three independent variables. Duncan's groupings in Table 5 show that SS is the best IP for the retailers and the entire supply chain; EOQ and POQ are in the next place; and SM is the worst one.

Table 6 lists the total cost performance for the entire supply chain and the retailers respectively, classified by EB, ED and IP. Under the perfect forecast (EB = 0 and ED = 0), demands faced by retailers become deterministic, thus, the deterministic lot-sizing rules (EOQ, POQ and SM) outperform the SS policy. Under the situations of EB = 0 and ED > 0, since the SS policy actually takes safety stocks into consideration when making inventory decisions, the SS policy can dramatically reduce the probability of the stockout and thus usually improves the supply chain performance. Furthermore, as ED increases from zero the 20%, the advantage of the SS policy over the deterministic lot-sizing rules also increases.

Table 6 TC and TCR classified by EB, ED and IP

Source		*EOQ*		*POQ*	
ED	*EB*	*RTC**	*RTCR**	*RTC**	*RTCR**
0	–5	116	125	107	112
	0	104	107	100	100
	5	107	112	105	108
	10	111	117	111	117
5	–5	121	134	124	137
	0	108	112	108	112
	5	108	112	108	112
	10	111	117	111	117
10	–5	132	149	134	153
	0	115	122	115	124
	5	110	115	110	116
	10	112	118	112	118
20	–5	147	173	150	177
	0	127	142	130	145
	5	118	127	120	130
	10	116	124	117	126
		SM		*SS*	
		*RTC**	*RTCR**	*RTC**	*RTCR**
0	–5	114	115	109	113
	0	107	105	105	107
	5	112	111	109	113
	10	116	118	113	121
5	–5	127	139	113	121
	0	112	115	107	111
	5	112	115	109	114
	10	116	119	114	121
10	–5	139	160	119	129
	0	119	127	111	116
	5	113	119	111	117
	10	115	121	115	122
20	–5	164	200	124	136
	0	138	158	117	126
	5	125	137	117	125
	10	120	130	119	129

Note: *RTC and RTCR are the relative total cost of the entire supply chain and the retailers respectively, with a base value of 100 representing the lowest TC and TCR.

The effect of retailers' inventory policies is also influenced by EB. The advantage of the SS policy over the deterministic lot-sizing rules diminishes or becomes week under a moderate value of EB. Nevertheless, our analyses suggest that the SS policy lead to the lowest total supply chain cost in most cases, therefore, in Subsection 4.4, we focus only on the SS policy under EB = 0 and ED > 0.

4.4 Impact of EOC

The ANOVA results in Table 4 reveal that the effects of EOC are significant according to all three performance measures. Duncan's groupings listed in Table 5 show that certain values of EOC can reduce the total cost for the supplier and the supply chain, but it hurts the retailers. As the EOC ratio increases from zero to one, TCR always increases; but the performances of TC and TCS are much more inordinate.

Figure 4 plots TC and TCS for IP = SS, EB = 0 and ED > 0. As the EOC ratio increases from zero to one, both TC and TCS roughly follow the rotated S-shaped curves: first, decrease to a local minimum for certain values of EOC with 0 < EOC < 1; then increase for a while; and finally, decrease to another local minimum with EOC = 1. When ED is small (ED = 5%), the first local minimum of TC is larger than the second one, which indicates that EOC = 1 is the best choice for the whole supply chain. However, when ED is large (ED = 10% or 20%), the first local minimum of TC is smaller than the second one, which indicates that a moderate EOC level (0 < EOC < 1) benefits the whole supply chain. In order to explain this phenomenon, we note that the curve of TCS follows the similar pattern with TC and TCS consists of inventory carrying cost (HCS), setup cost (SCS) and backorder cost (BCS, including transportation cost) for the supplier. Since EOC affects SCS only slightly, we examine the impact of EOC on HCS and BCS in more details.

Figure 4 Interactive effects of EOC and ED on TC and TCS, when IP = SS, EB = 0 and ED > 0

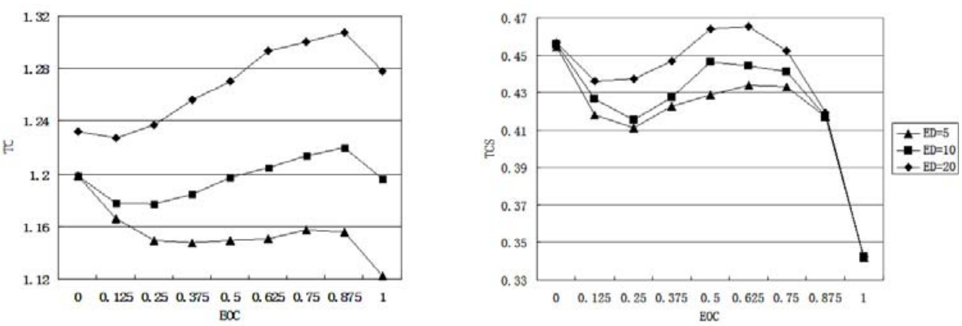


Figure 5 plots the effects of EOC on HCS and BCS respectively, categorised by ED. Generally speaking, EOC reduces the supplier's risk caused by demand uncertainty, which allows the supplier to improve its production decisions. Moreover, since the supplier uses periodical review (s, S) policy to make production decisions, EOC can significantly reduce its safety stock. Consequently, HCS gradually declines as EOC increases from zero to one. The effect of EOC on BCS is much more intricate, which has a very similar pattern to the TCS shown in Figure 4. As we know, BCS is closely related to the service level of the supplier. A lower BCS implies a higher service level; and a higher BCS implies a lower service level. Therefore, we further examine the supplier's service level to ascertain the impact of EOC on BCS.

Figure 5 Interactive effects of EOC and ED on HCS, when IP = SS, EB = 0 and ED > 0

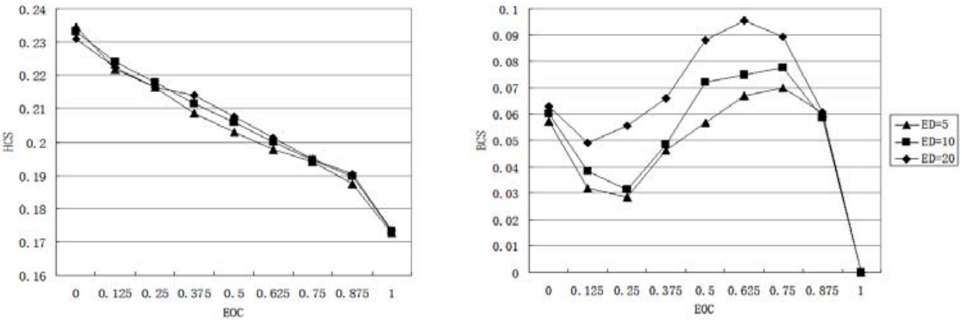
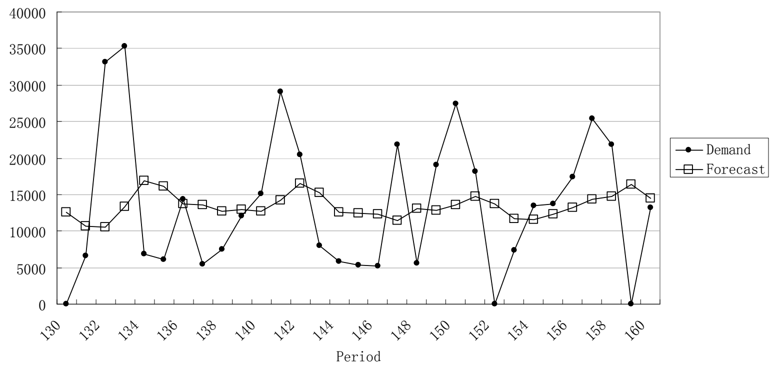


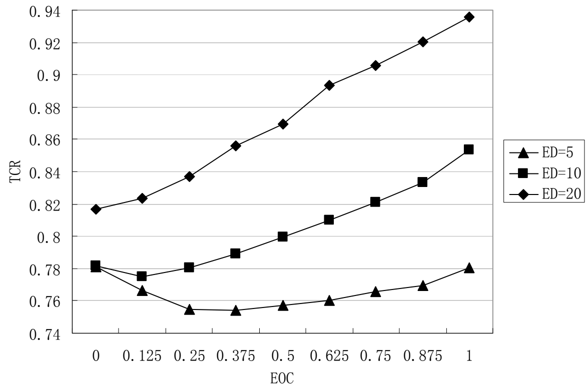
Figure 6 Demands and forecasts for the supplier in a simulation run



According to the simulation procedures, each retailer places its order to the supplier periodically, no matter what IP he used. It is very possible that he infrequently places orders to the supplier in several consecutive periods and then suspends ordering for a long time. For the supplier, sometimes, he receives an amount of orders in a period, but sometimes, he receives only a very few orders. Hereby, the trend of supplier's demands undulates just like pulses as shown in Figure 6, where the data was from a simulation run. The supplier forecasts demands using the simple moving average method, which in fact predicts the average demand. For a small value of EOC, only the first several periods' orders are committed by the retailers and the risk caused by demand uncertainty in these periods is dismissed. Meanwhile, the supplier has to forecast the retailers' orders for the rest of many periods in the planning horizon (we will call the periods in which orders should be forecasted as the supplier's forecasting horizon hereafter) and the forecasting model he used can bring him a relatively exact forecast for the demand. Therefore, a small value of EOC can improve the supplier's service level. However, for a larger value of EOC (but less than one, e.g., EOC = 3/4), most of the periods' orders are committed by the retailers and the supplier has to forecast retailers' orders in a very few periods (i.e., the supplier's forecasting horizon is very short, e.g., only two periods). As the supplier sometimes receives a large number of orders in a few consecutive periods (e.g., two periods) and receives no orders in other periods, he cannot exactly predict this type of demands and shortages occur in the supplier's site. These effects of EOC reduce the supplier's service level, which increases TCS directly and TCR indirectly. Finally, when EOC is raised to one, demands for the supplier in the whole planning horizon becomes deterministic and no need for him to forecast retailers' orders any more, thus, he achieves the best service level. Therefore, BCS have the rotated S-shaped pattern as shown in Figure 5 and this also explains the effect of EOC on TCS as shown in Figure 4.

Finally, we note that the performance of EOC according to TCR is also influenced by ED. Figure 7 plots TCR under various levels of EOC categorised by ED. As we know, EOC effectively increases the supplier's service level. If there is a stockout in the supplier's site in a period, retailers' orders will be backlogged, which always causes shortage penalty to the retailers who placed orders in that period. As we analysed before, it will lead to a higher shortage penalty in that period and a higher inventory carrying cost in later periods for the retailers. For a small value of ED (ED = 5% or 10%), a moderate EOC level affects the retailers ordering decisions only slightly, but it helps the supplier to improve its service level, which indirectly reduce the shortage penalty and holding cost for the retailers. Under this situation, a moderate EOC can bring the retailers a better performance. But for a large value of ED (ED = 20%), EOC affects the retailers seriously. In this situation, TCR always increases as EOC increases.

Figure 7 Interaction of EOC and ED on TCR when IP = SS, EB = 0 and ED > 0



From above observations about EOC, we conclude that for a small value of ED, a moderate EOC benefits both the supplier and the retailers, and EOC = 1 could have the best performance for the whole supply chain. However, for a large value of ED, EOC benefits the supplier and the entire supply chain but hurts the retailers and a moderate EOC level (0 < EOC < 1) could have the best performance for the whole supply chain. The larger the ED, the narrower the reasonable ranges of EOC which can be chosen to benefit the supply chain. In particular, the strategy of using a larger EOC but less than one (i.e., 1 – EOC is a small positive value) which leads to a very short forecasting horizon for the supplier, mostly hurts both the supplier and the retailers, and thus it is should not be accepted.

4.5 Sensitivity analyses

We also performed a series of sensitivity analyses to explore whether the findings of the base case still apply in different situations where the environmental factors [cost structure (CS) and the supplier's lead time (PT)] are changed.

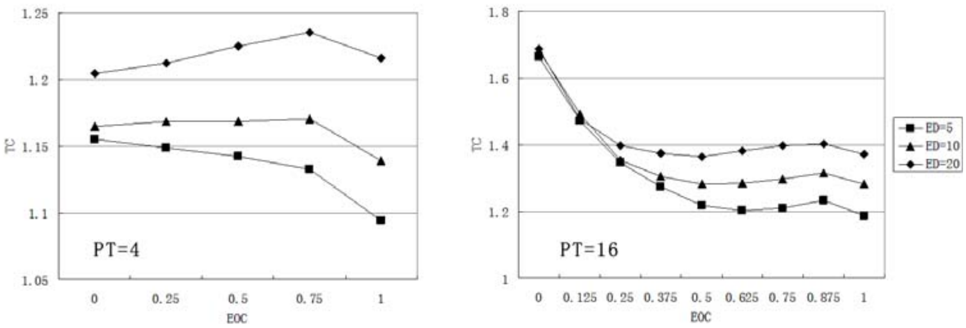
4.5.1 Cost structure

As we summarised in Table 1, we designed four types of cost structures. Case A is the base case featuring low inventory carrying cost and low shortage penalties. In Case B, the inventory carrying cost are the same as in Case A, but the shortage penalty is raised to five times higher than that in Case A for the supplier and twice higher than that in Case A for the retailers. In Case C, the shortage penalties remain the same as in Case A, but we double the inventory carrying cost for both the supplier and the retailers. In Case D, high inventory carrying cost and high shortage penalties are adopted. The key findings from the base case (CS = A) still hold under Cases B, C and D. To save space, we omit to present the detailed results here.

4.5.2 Supplier's production lead time

Sensitivity analysis is also conducted to test the effects of the supplier's production lead time (PT). Since PT is set at eight periods in the base case, here, we test two other values of PT: four and 16 periods. Please note that when PT is four periods, EOC can only have five levels, which are zero, 1/4, 1/2, 3/4 and one. While most of the findings are very similar to those found in the base case (PT = 8), we notice that PT influences the cost savings that can be achieved when adopting EOC. Figure 8 plots the total cost of the whole supply chain under different combinations of EOC and ED when PT = 4 and 16, respectively. For all these three PT levels, we can see EOC can enhance the supply chain performance when PT is long or forecasting errors are tiny. When PT has a large value (e.g., PT = 16), EOC can bring great benefits to the whole supply chain even when forecasting errors are huge (ED = 20%). Similarly as we suggested in the base case, if using EOC results in a short forecasting horizon for the supplier, then EOC is not a wise strategy in any levels of PT.

Figure 8 Interactive effects of EOC and ED on TC under PT = 4 and 16



5 Conclusions and managerial implications

This paper explores the value of practicing EOC in supply chains with (s, S) policies and lost sales. It also examines the impact of forecasting errors and selection of inventory policies for the retailers on the performance of the supply chain. Computer simulations are conducted for a supply chain with one supplier who has a production lead time and multiple retailers with demand uncertainty. The research extends existing literature on EOC in two aspects:

1 both the supplier and retailers use the periodical review (s, S) policy, instead of the deterministic lot-sizing rules, to make their inventory decisions

2 when retailers stock out, the shortages become lost sales instead of backorders.

The findings from this research enhance our understandings on the effects of EOC in supply chain management.

Our research leads to the following conclusions and managerial implications:

1 The selection of retailers' inventory policies is one of the most important tasks in the supply chain management, which can significantly affects the cost measures of not only the retailers, but also the supplier. The use of periodical review (s, S) policy usually leads to a better supply chain performance compared with the deterministic lot-sizing rules. Furthermore, using the periodical review (s, S) policy can effectively reduce the influence of forecasting errors.

2 A carefully chosen EOC strategy can gain considerable cost savings. EOC can generate significant cost savings to both the supplier and the whole supply chain when retailers' forecasting errors are small or the supplier's forecasting horizon is long. However, if the supplier's forecasting horizon is very short and the retailers' forecasting errors are large, EOC hardly enhances the performance of the supply chain. Therefore, in order to reach the best performance, the EOC periods should be set to some periods less than the production lead time when forecasting errors are large; however, they should be set to the same as the supplier's production lead time when forecasting errors are small.

3 Sensitivity analyses show that the findings are almost the same in the environments where the cost structure or the production lead time is different.

These findings suggest that EOC can be a fruitful avenue for enhancing supply chain coordination and reducing total cost in supply chains with lost sales. In order to choose a wise EOC strategy to gain a better performance, managers should consider retailers' forecasting errors, the selection of inventory policies and other environment factors.

The limitations of the study should be noted and there are several directions for further research. First, we only considered a simple two-level supply chain with special cost structures. More works are needed to verify whether the findings from this research can be extended to more general supply chain systems. Second, the supplier does not subject to any capacity constraints in our model, which is not realistic in most practical business. Considering a capacitated supplier with a production lead time may lead to new findings. Finally, we do not consider any forms of incentives to entice retailers to commit orders earlier. Incentive schemes, e.g., price discounts provided by the supplier to the retailers, will be very interesting to investigate.

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