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The role of forecasting on bullwhip effect for E-SCM applications

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Abstract

The bullwhip effect represents the information distortion in customer demand between orders to supplier and sales to the buyer. Demand forecasting is one of the main causes of the bullwhip effect. The purpose of this study is to analyze the impact of exponential smoothing forecasts on the bullwhip effect for electronic supply chain management (E-SCM) applications. A simulation model is developed to experiment the different scenarios of selecting right parameters for the exponential smoothing forecasting technique. It is found that longer lead times and poor selection of forecasting model parameters lead to strong bullwhip effect in E-SCM. In contrast, increased seasonality helps to reduce the bullwhip effect. The most significant managerial implication of this study lies in the need to reduce lead times along the E-supply chain to mitigate the bullwhip effect. While high seasonality would reduce the forecast accuracy, it has a positive influence on the reduction of bullwhip effect. E-SCM managers are therefore strongly suggested to utilize exponential smoothing by selecting lower values for α and β and a mid-value for γ to keep the bullwhip ratio low, while at the same time to increase forecast accuracy.

Keywords: Bullwhip effect; Forecasting; Exponential smoothing; E-SCM

1. Introduction

Despite shorter product life cycles and tight product/service costs, the idea of "any product any time any place" has now become possible through advancements in communication and transportation technologies. The contemporary businesses faced with these challenges have been more effectively coping with uncertainties emerging in their supply chains. Uncertainty is generally defined as unknown future events that cannot be predicted quantitatively within useful limits, thus making the occurrence of uncertainty unpredictable (Cox and Blackstone, 1998). The sources of uncertainty lie in the process of matching demand

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with supply. The following sources of uncertainty, which include delivery lead times, manufacturing yields, transportation times, machining times and operator performances (Simchi-Levi et al., 2003), all lead to supply uncertainty that has significant impact on chain performance. On the other hand, the difficulties in predicting customer needs and wants in a given period constitute the main source of demand uncertainty that a good forecast may cope with this uncertainty. In fact, the ultimate success lies in the ability to manage the demand uncertainty with the existent supply capabilities.

It has been emphatically pointed out that understanding and practising supply chain management (SCM) has become an essential prerequisite to be able to manage demand uncertainties and to growing profitably in the global competitive race (Power et al., 2001; Moberg et al., 2002). SCM includes a set of approaches and practices to reduce the uncertainty along the chain through enabling a better integration among suppliers, manufacturers, distributors and customers (Koh et al., 2007). It is "the efficient management of the end-to-end process, which starts with the design of the product or service and ends with the time when it has been sold, consumed, and finally, discarded by the consumer" (Swaminathan and Tayur, 2003, p. 1387). Apart from traditional SCM practices, there are several tools and techniques of electronic SCM (E-SCM) to diminish uncertainty in E-supply chains, which inter alia include information sharing, third-party logistics (3PL) providers, centralized planning, strategic alliances and E-commerce logistics (ECL). Of these tools, 3PL and ECL applications have been increasingly gaining popularity among contemporary businesses (Coyle et al., 1996; Lambert et al., 1999).

Given the imperatives of intense global competition, the buyers dominate the market and present their personalized and customized requirements. This makes the demand change rapidly and difficult to forecast (Ying and Dayong, 2005). By reducing uncertainty and improving efficiency to logistics management, 3PL could increase supply chain effectiveness through the following ways (Simchi-Levi et al., 2003; Maloni and Carter, 2006): (1) enabling the company to focus on its core competencies; (2) providing flexibility in adaptation to new technology, resource and workforce size; and (3) accessing to expertise of 3PL providers on the outsourced activity and their economies of scale. 3PL is a type of services of multiple distribution activities provided by an external party (assuming no ownership of inventory) to accomplish related functions that are not desired to be rendered and/or managed by the purchasing enterprise (Sink et al., 1996). In other words, 3PL refers to the outsourcing of transportation, warehousing and other logistics-related activities to a 3PL provider that were originally performed in-house. With the use of 3PL for all or part of an enterprise's logistics operations, significant reduction in logistics cost can be achieved while improving service quality.

ECL is defined as the "impact of the Internet on the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services, and related information from the point-of-origin to the point-of-consumption in order to meet customers' requirements" (Giménez and Lourenço, 2004, p. 3). ECL is recognized as a subset of E-SCM that refers to "the impact that Internet has on the *integration* of key business processes from end user through original suppliers that provides products, services and information that *add value* for customers and *other stakeholders*" (Giménez and Lourenço, 2004). E-SCM enhances the revenue through direct sales to customers with 24/7 access from any location, personalization and customization of information, faster time to market, flexible pricing and efficient fund transfer; and reduces the cost through better coordination with information sharing, lower delivery cost and time, less product handling, lower facility and processing costs, reduced inventory cost with centralization, and postponement product differentiation (Chopra and Meindl, 2001). According to Swaminathan and Tayur (2003), the Internet has influenced SCM in three ways: (1) increased use of ERP and advanced planning and optimization solutions; (2) ability to access real-time information in order to make real-time decisions; and (3) integrate information and decision making across different functional units. As a result, it diminishes the uncertainty with the availability of more information.

Risk-pooling, mass customization and dynamic pricing are some of the SCM issues heavily influenced by E-business applications. Although Internet applications introduce new perspectives to traditional issues and enhance capabilities of SCM, many SCM-related issues are yet to be resolved. Among some of these are keeping buffer inventory or capacity for guaranteeing the certain service levels and classical trade-off between fix and variable costs in procurement decisions (Swaminathan and Tayur, 2003). The need for accurate demand forecasting, for instance, is not completely eliminated. Sharing point-of-sales (POS) data with chain partners and analyzing it through data mining techniques may help to improve forecast accuracy, though for many decisions we still rely on the forecasts.

Demand forecasting is an essential tool for production and inventory planning, capacity management and the design of the customer service levels. Many demand-forecasting techniques rely on the historical data and assume the validity of the past demand patterns for the near future. Due to high sensitivity of the forecast values to the most recent occurrences, this approach, in general, produces high (low) demand forecast values following high (low) demand periods. At the same time, customer demand is passed to the wholesalers, distributors or manufacturers in the form of retailers' order, which is actually the demand for higher-level chain partners. Demand forecasts in practice, however, are rarely accurate and they become even worse at higher levels of the supply chain. In most supply chains, individual chain members attempt to rationalize their order sizes with economical batching decisions, though this creates a distortion on the real customer demand and misleads the upper-level supply chain members with respect to demand. Promotions and price fluctuations also contribute to demand distortion. The need to forecast the demand at each level of the supply chain amplifies the forecast errors, the so-called bullwhip effect, along the whole chain. Lee et al. (1997a) label this as double forecasting. Therefore, it is extremely important to establish a proper demand forecast system to reduce the bullwhip effect.

The bullwhip effect, also known as Forrester or whiplash effect is one of the key areas of research in SCM applications. It represents the phenomenon where orders to supplier tend to have larger variance than sales to the buyer, and customer demand is distorted (Lee et al., 1997a, b). This demand distortion also propagates to upstream stages in an amplified form. In return, high inventory levels and poor customer service rates along the supply chain constitute typical symptoms of bullwhip effect. In addition, production and inventory holding costs as well as lead times increase, while profit margins and product availability decrease (Chopra and Meindl, 2001, p. 363). Metters (1997) empirically showed that elimination of the bullwhip effect might increase product profitability by 10–30 percent depending on the specific business environments.

Within the context of E-SCM applications, this study essentially analyzes the impact of demand forecasting on the bullwhip effect. Based on a simulation model, a two-stage E-supply chain is examined using exponential smoothing forecasting on the bullwhip effect under linear demand assumption with seasonal swings. While in earlier research, Chen et al. (2000a, b) analytically examined the similar problem for autoregressive demand structures and linear demand, they did not take into account the demand seasonality. This study therefore fills this gap by developing a simulation model for E-SCM applications, which experiments the different scenarios of selecting suitable parameters for exponential smoothing forecasting, lead time and demand seasonality.

The remainder of this study is organized as follows. The next section reviews the previous literature related to demand uncertainty in E-SCM practices with special emphasis on ECL and 3PL applications. Section 3 explains the development of an E-supply chain simulation model to test demand forecast based on exponential smoothing. Setting of experimental design is identified in Section 4, followed by simulation results. Conclusions are in the final section.

2. Literature survey

Uncertainty can be defined as unpredictable events in a supply chain that affects its planned performance (Koh and Gunasekaran, 2006). Owing to high transactional volume in a an E-supply chain, demand uncertainty caused by inaccurate forecast would feed into information exchange in the network, which in turn would result in the bullwhip effect. Such an effect may affect the ability of ECL and 3PL applications in meeting the expected delivery performance of goods and services.

The bullwhip effect was first noticed and studied by Forrester (1961) in a series of simulation analysis. He named this problem as "demand amplification". He further concluded that the problem of the bullwhip effect stemmed from the system itself with its policies, organization structure and delays in material and information flow, not stemmed from the external forces. Later, Sterman (1989) studied the bullwhip effect by playing the "beer distribution game" with students. He noted that misperception of feedback loops and irrational reaction of decision makers to a complex and tacit system created the bullwhip effect. As people have difficulties to realize the impact of their ordering decisions due to complexity of the system and the time lags between ordering and receiving, Sterman (1989) suggests that operations managers be provided necessary training on the bullwhip effect. Lee et al. (1997a, b), however, indicate that bullwhip effect is present, even if all members of the supply chain behave in an optimal manner unless the supply chain is redesigned with different strategic interactions. Their analytical study points out that the bullwhip effect stems mainly from four factors: demand forecasting, order batching, price fluctuations, and rationing and shortage gaming. While supporting this view on the causes of the bullwhip effect, Miragliotta (2006) criticizes the mechanism generating the bullwhip effect. In their review of bullwhip effect, Geary et al. (2006) emphasize the following causes initially suggested by Jack Forrester and Jack Burbidge, twin pioneers of modern supply chain knowledge: control systems, activity times in the chain, level of information transparency, the number of echelons, synchronization and multiplier effect.

Following Lee et al. (1997a), several other researchers have also concentrated on the causes of the bullwhip effect in order to understand their impacts on supply chain. Of these causes, the major emphasis has been placed on demand forecasting. Researchers relying on different methodologies have constructed various models to explore the impact of demand forecast. For example, Chen et al. (2000a, b) used statistical methods and Anderson et al. (2000) adopted system-thinking methodology, while Dejonckheere et al. (2003, 2004) and Disney and Towill (2003a) used control-engineering methodology. All of these studies concentrated predominantly on the forecasting methods of moving average, simple exponential smoothing and double exponential smoothing. Their results indicated that the number of observations used in moving average should be high in order to lower the bullwhip effect. Moreover, lower values of smoothing parameters (α, β) are required in exponential smoothing forecasting. While these studies offer a number of useful implications for E-SCM practitioners, they do not provide all the information required as none of these studies considered seasonality in their models.

For AR(1) demand processes using order-up-to inventory policy, Chen et al. (2000a) quantified the bullwhip effect for moving the average forecasting model in a two-level supply chain. Their findings support the significance of reducing lead times to mitigate the bullwhip effect. Under similar assumptions, Zhang (2004) derived the optimum forecasting procedure minimizing the mean-squared forecasting error (MMSE) where MMSE forecast leads to lowest inventory cost under the given conditions. Reduction of lead time has the most significant impact on the decline of the bullwhip effect under MMSE forecasts when the demand autocorrelation is positive and away from zero or one. If demand correlation is negative, exponential smoothing provides the most significant impact on the bullwhip effect for reduced lead times. Chen et al. (2000b) also investigated the double exponential smoothing forecasting technique for demand process with a linear trend. They emphasized the importance of selecting relatively lower values for smoothing parameters (α, β) and reducing lead times to diminish the bullwhip effect. They also stated that a retailer who forecasts a linear demand processes faces relatively higher-order variability as compared with one who forecasts a stationary demand process. This variability also does not depend on the magnitude of the linear trend. Another important finding emerging from this study is that exponential smoothing method also produces more variability compared with the moving average method.

Zhao et al. (2002) investigated the impact of forecasting models, demand patterns and capacity tightness of the supplier on the performance of the supply chain in terms of total cost and service level. Their model has included one capacitated supplier with setup and backorder costs and four retailers replenishing according to economic order quantity model. Their findings have emphasized the impact of the accuracy of forecast models on the value of information sharing. The supplier can improve its total costs and service level through information sharing in all cases, while total costs and service level for retailers may even become worse under information sharing when capacity tightness is low.

In fact, demand forecasting has been recognized as only one of the four main causes of the bullwhip effect (Lee et al., 1997a); thereby using a smoother forecasting policy is not a unique remedy for the bullwhip effect. There are also other proposed strategies, which can be summarized as follows: sharing POS data with trading partners (Dejonckheere et al., 2004; McCullen and Towill, 2001, 2002; Chen et al., 2000a, b; Mason-Jones and Towill, 2000; Towill, 1997); echelon elimination (e.g. implementing vendor managed inventory) (Disney and Towill, 2003b; Forrester, 1961); lead-time reduction (Forrester, 1961; Lee et al., 1997a; Machuca and Barajas, 2004; Anderson et al., 2000); training decision makers for more rational decisions (Sterman, 1989); and designing robust systems that minimize human interactions (Disney et al., 2004).

3. The supply chain simulation model

This study concentrates on a two-stage E-supply chain that consists of one supplier and one on-line retailer, which is shown in Fig. 1. The supplier provides a single product for the on-line retailer, while the on-line retailer fulfills the requirements of the on-line customers at the marketplace through the distribution center.

Fig. 1 shows that at the beginning of each period, t, the retailer receives the delivery of the supplier, which was ordered L periods ago by the retailer (the lead time is L periods). Meanwhile, the actual customer demand emerges at the marketplace. The retailer fulfills the customer demand (plus back-orders if there is any) by on-hand inventory, and any unfulfilled customer demands are backordered. After the actual customer demand is satisfied, the retailer analyzes the historical demand data and makes a demand forecast for future periods. Based on this demand forecast, the retailer decides how many units to order from the supplier using its inventory control policy. In this case, we assume that the retailer follows a simple "order up to policy" to manage its inventory in which the order

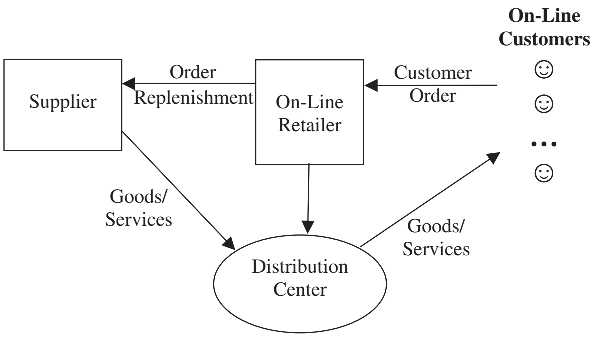

Fig. 1. Simulated supply chain model.

up to point, S_t, is estimated from the observed demand as follows:

$$S_t = \hat{D}_t^L + z\hat{\sigma}_t^L, \tag{1}$$

where $\hat{D}_t^L$ is an estimate of the demand over lead time, $\hat{\sigma}_t^L$ is an estimate of the standard deviation of the L period forecast error and z is a constant chosen to meet a desired service level. It should be noted that z is also known as the safety factor. Here, it is assumed that the on-line retailer chooses a 95 percent fill rate and selects a threshold z value of 1.65.

We assume that the supplier delivers all orders of the on-line retailer after a fixed lead time (L) so that it will simplify the retailer's replenishment policy. This is, however, not a very realistic assumption. For example, when an order of an on-line retailer exceeds a supplier's capacity, either the order may be cut-off, or the lead time may be extended where both will in turn increase the order variability of the on-line retailer (demand of the supplier) as well as the bullwhip effect. Since the model explicitly analyzes the impact of longer lead times and focuses on the role of forecasting models on the bullwhip effect, this is not likely to cause any significant diversion from the model. A similar assumption has also been made in several other studies in the prior literature (Aviv, 2002; Chen et al., 2000a, b). In practice, the supplier needs to adjust its capacity to match the demand in the long run where short-term shortages can be negligible.

3.1. Generation of on-line customer demand and on-line retailer's demand forecast

It is assumed that the on-line retailer has a linear demand process with seasonal swings. Different demand structures for the on-line retailer in the simulation model are generated using the following formula, in fact, a very similar form for an additive time series is also used by Zhao et al. (2002):

$$D_t = (\text{base} + \text{slope} \times t) \times \left(\frac{[\text{season} + \sin(2\Pi/52 \times t)]}{\text{season}} \right) + \text{noise} \times \text{snormal}(), \tag{2}$$

where D_t is the demand in week t, snormal() is a standard normal random number generator between 0 and 1. *Base*, *slope* and *noise* are typical linear demand parameters and are assigned the values of 1000, 2 and 100, respectively. *Season* represents magnitude of seasonality. In order to evaluate the impact of seasonality on the bullwhip effect, three types of demand structures representing different levels of seasonality are used: low, medium and high. For each level of seasonality in Eq. (1), the respective values of 5, 15 and 30 are assigned accordingly.

Since both linear trend and seasonality exist together in the demand model, Winter's (triple exponential smoothing) method for forecasting is employed in the simulation model. Thus, the on-line retailer uses Winter's method to forecast the demand over lead time. This forecasting method

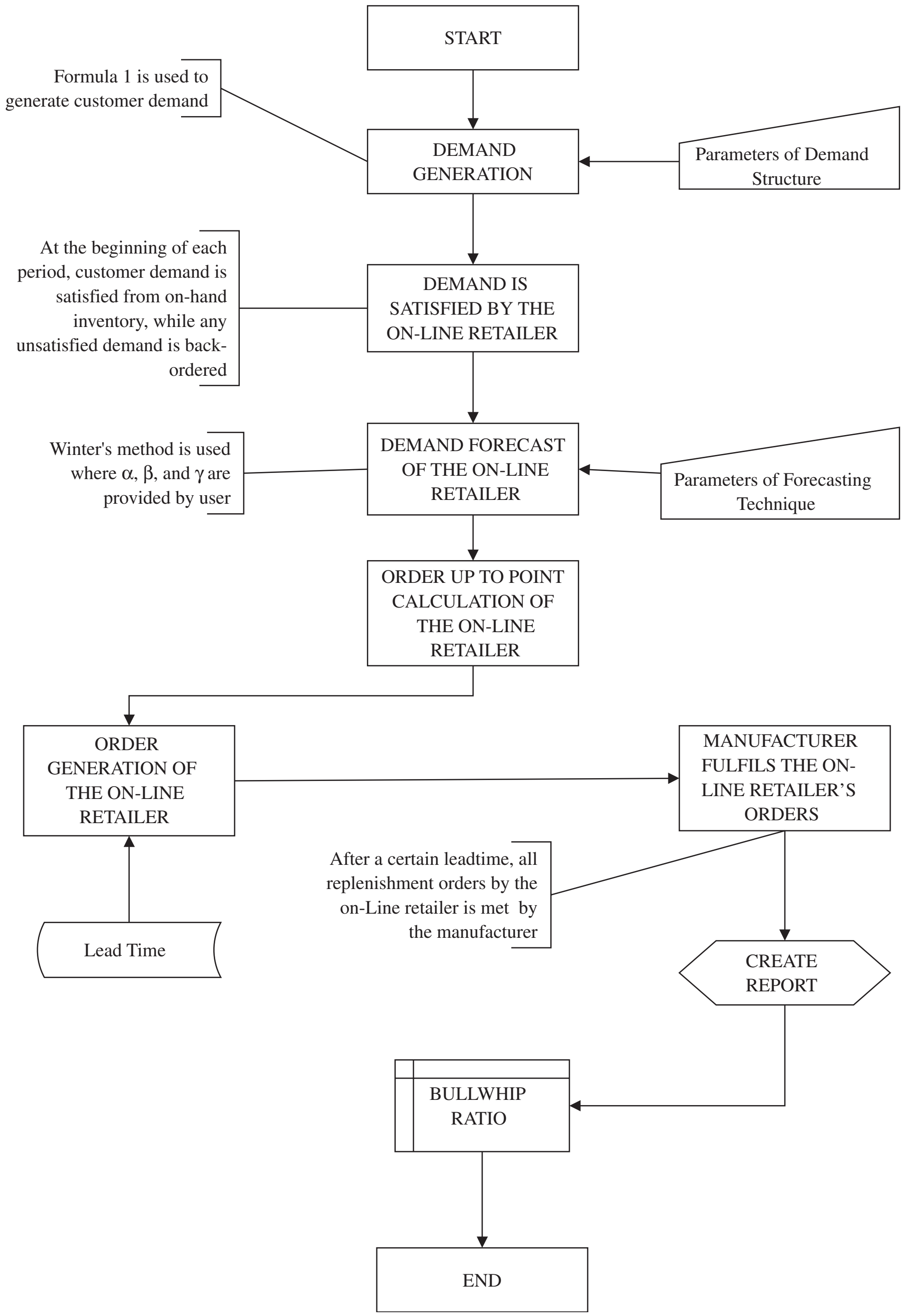

Fig. 2. Flowchart of simulation model.

requires three smoothing parameters to update level, trend and seasonal components of the demand, which are represented by alpha (α), beta (β) and gamma (γ), respectively. More detailed information on this forecasting method is provided in Abraham and Ledolter (1983, p. 170).

3.2. *Verification and validation of simulation*

A two-stage E-supply chain is simulated in Microsoft Excel. Simulation logic along with a flowchart are shown in Fig. 2. To verify that the program performs as intended, the conceptual model is divided into three parts: demand generation, forecasting and calculation of inventory levels. Each part is then debugged individually to confirm whether the findings are in line with sample solution problems. A combined simulation model is also traced and tested with the results computed manually.

In order to validate the simulation output, the random demand variables generated by Excel is plotted on a scatter diagram. It is validated that the demand function in Eq. (1) is generated. The supply chain model above was simulated for 520 weeks. The initial parameters of the forecasting model were estimated by the first 156 weeks of simulation run, which was removed later from the output analysis to eliminate the warm-up period effect. Therefore, the rest of the data were used for effective simulation output analysis. In addition, ten replications for each combination of the independent variables were conducted to reduce the impact of random variations.

We also performed the sensitivity analysis for demand parameters by changing the values of *base*, *trend* and *noise*. It has been further validated that the variation in the demand parameters does not affect our findings. Therefore, only one combination of these parameters is selected to perform the analysis.

4. Experimental design

The purpose of the experimental design is twofold: (1) analyzing the impact of the smoothing parameters, lead time and strength of seasonality on the bullwhip effect and (2) examining the interaction of the smoothing parameters with lead time and seasonality. Therefore, three groups of independent factors are investigated through the experimental design. The number of levels of these factors with their respective values is listed in Table 1. The values of α and β parameters used in the exponential smoothing are suggested to be less than 0.5 in order to obtain better forecast values from Winter's forecasting model (Winston, 1993, p. 1268). The levels of these parameters are set accordingly.

Table 1
Independent factors of the experimental design

Independent factors	Levels		
	1	2	3
Smoothing parameters			
Alpha (α)	0.01	0.25	0.50
Beta (β)	0.01	0.25	0.50
Gamma (γ)	0.01	0.25	0.50
Strength of seasonality	Low	Medium	High
Lead time	1 week	3 weeks	5 weeks

The *bullwhip ratio* is denoted as the dependent variable of the design of experiment. It indicates the ratio of variance of the orders realized by the manufacturer to the variance of the demand observed by the retailer as in Eq. (3):

$$\text{Bullwhip ratio} = \frac{\text{Var(Order)}}{\text{Var(Demand)}}. \tag{3}$$

5. Simulation output analysis

Out of 520 weeks of the simulation of the supply chain model above, data from the remaining 364 weeks (from weeks 157 to 520) for ten replications were used for simulation output analysis. Through ANOVA tests, the output from the simulation experiments was compared based on mean measures with respect to three different levels of smoothing parameters, lead time and seasonality. The ANOVA test results for the main and interaction effects are shown in Table 2.

5.1. *Main effects*

ANOVA test results in Table 2 indicate that the bullwhip effect is significantly influenced by the smoothing parameters, lead time and seasonality ($p<0.05$), suggesting that all three factors determine the degree of information distortion along the supply chain. Once we have noted that all independent factors of the experimental design significantly influence the bullwhip effect, we then conducted

Table 2
Selected ANOVA results[a]

Source	Mean square	F	Sig.
Alpha	104.7684	44828.4	0.0000
Beta	14.0638	6017.6	0.0000
Gamma	0.4636	198.3	0.0000
Lead time	34.7446	14866.5	0.0000
Seasonality	12.0279	5146.5	0.0000
Alpha * beta	3.3380	1428.3	0.0000
Alpha * gamma	0.0120	5.1	0.0004
Alpha * lead time	8.7309	3735.8	0.0000
Alpha * seasonality	0.7507	321.2	0.0000
Beta * gamma	0.0221	9.4	0.0000
Beta * lead time	1.5905	680.5	0.0000
Beta * seasonality	0.0458	19.6	0.0000
Gamma * lead time	0.0038	1.62	0.1668
Gamma * seasonality	0.0061	2.6	0.0337
Lead time * seasonality	0.1378	58.9	0.0000

[a]Log transformation of dependent variable is conducted in order to satisfy the ANOVA assumptions.

Table 3
Homogeneous subsets of each independent variable

Variable	Level	N	Subset			Sign.
			1	2	3	
Alpha	0.01	810	1.5278			1.000
	0.25	810		4.7314		1.000
	0.50	810			11.9877	1.000
Beta	0.01	810	3.2035			1.000
	0.25	810		5.6520		1.000
	0.50	810			9.3914	1.000
Gamma	0,25	810	5.7972			0.208
	0.50	810	6.0406			
	0.01	810		6.4091		1.000
Lead time	1 week	810	2.3932			1.000
	3 weeks	810		5.1418		1.000
	5 weeks	810			10.7119	1.000
Seasonality	High	810	3.7289			1.000
	Medium	810		6.9463		1.000
	Low	810			7.5718	1.000

multiple comparisons tests in order to understand how each of these independent variables would affect the bullwhip effect. While there are a number of multiple comparisons tests, we have conducted Tukey's procedure in this study due to its wider acceptance (Devore, 1995, p. 400). The results of Tukey's procedure are shown in Table 3, where homogeneous subsets are produced.

Table 3 indicates that any increase in the values of α and β parameters, and lead times lead to an increase in the bullwhip effect. In contrast, the impact of the γ parameter and seasonality on the bullwhip effect displays a different pattern. As the strength of seasonality increases, the value of the bullwhip ratio decreases, as shown in Table 3. This might be explained by the fact that the forecasting method used in the model performs better for higher levels of seasonality. In other words, the variation generated by the seasonality cancels out the variability created by the bullwhip effect. When the γ parameter is taken into account, however, Table 3 reveals that the bullwhip ratio becomes the smallest when the γ parameter is 0.25 and the largest when it is 0.01. This result confirms the existence of a U-type relationship between the γ parameter and the bullwhip ratio. It is most likely that there are slight decreases in the bullwhip ratio as the value of the γ parameter increases up to a point, and then it starts to increase with higher values of γ parameter. The γ parameter will be analyzed further in Section 5.4.

5.2. Interaction between smoothing parameters and lead time

The interaction effect between smoothing parameters and lead time is shown in Fig. 3. Fig. 3 indicates that α and β parameters act very much similar on the bullwhip ratio against lead times. When the lead time is low, there is not much difference on the bullwhip ratio based on the selection of the α and β parameters. However, the bullwhip ratio increases very quickly as the lead time and the values of the α and β parameters increase. Therefore, the values of the α and β parameters in the forecasting model should be selected small enough to keep the bullwhip effect low.

When we consider the interaction of the γ parameter with lead time, Fig. 3 indicates a different situation that longer lead times always lead to huge increases in the bullwhip ratio independently from the value of the γ parameter. Therefore, we can state that the γ parameter cannot contribute sufficiently to reduce the negative impact of longer lead times.

5.3. Interaction between smoothing parameters and seasonality

Fig. 4 shows the interaction effect between smoothing parameters and seasonality. It may be readily apparent from Fig. 4 that interactions of the

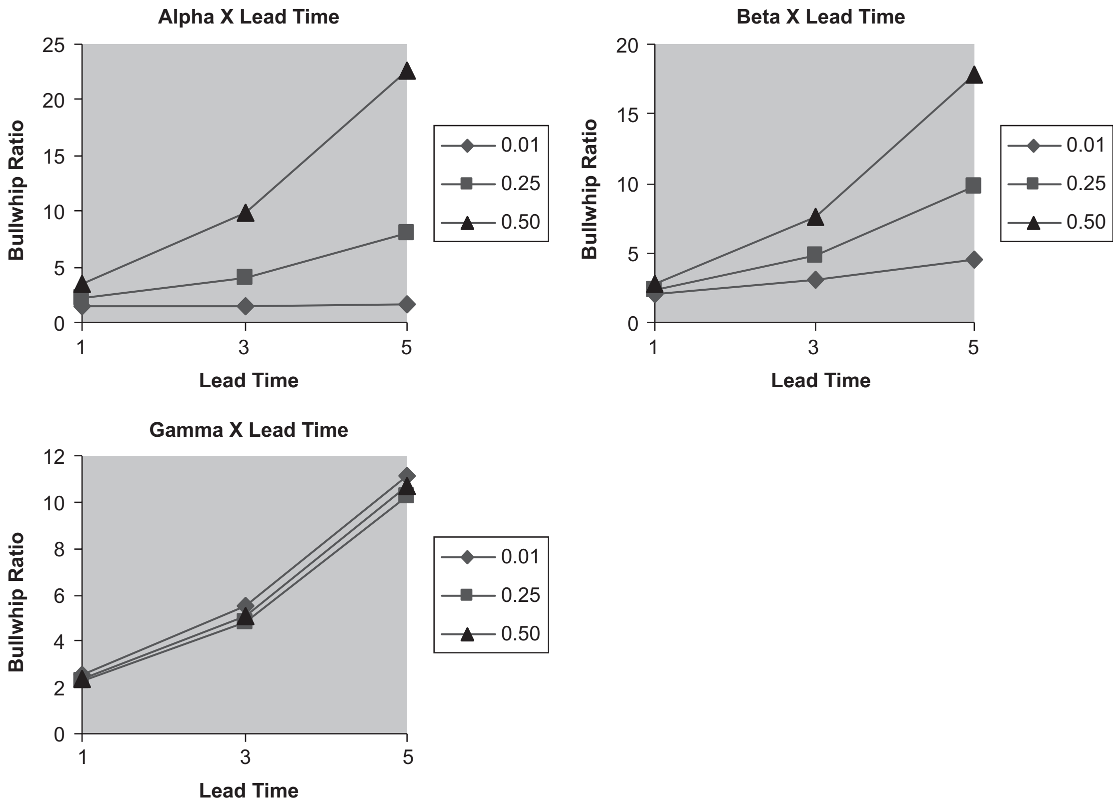

Fig. 3. Interaction effect between smoothing parameters and replenishment lead time.

α and β parameters with seasonality have some similarities; selection of relatively lower values for the α and β parameters enables one to reduce the bullwhip ratio at all levels of demand seasonality. Since the bullwhip effect is lower under high levels of seasonality as compared with the one under low levels of seasonality, the selection of relatively lower values for α and β parameters becomes crucially important to be able to reduce the bullwhip ratio under low demand seasonality. On the other hand, Fig. 4 reveals that selection of the γ parameter does not have a significant impact on each seasonality level individually, since seasonality has a much stronger influence on the bullwhip effect.

5.4. *Further analysis of the γ parameter*

In order to understand better the influence of γ parameter on the bullwhip ratio, we further analyze γ parameter for various levels ranging from 0.01 to 0.91 with increments of 0.10 while keeping all other parameters of the model constant. This analysis clarifies that the relationship between the bullwhip effect and the γ parameter is in a quadratic form as shown in Fig. 5. Hence, the value of the γ parameter should be selected in a way to minimize bullwhip effect.

6. Conclusion

This study has provided a detailed analysis of the impact of the exponential smoothing forecasting technique on the bullwhip effect for a linear demand structure with seasonal swings within the context of ECL applications. Although Chen et al. (2000a, b) initially examined the similar problem analytically for autoregressive demand structures and linear demand, they did not consider the demand seasonality in their work. A simulation model developed here examined linear demand processes with seasonal swings in order to observe the interaction between the forecasting parameters and the bullwhip effect. Based on the simulation analysis, this study noted a highly significant finding that high levels of seasonality have a positive impact on reducing the bullwhip effect. In other words, the

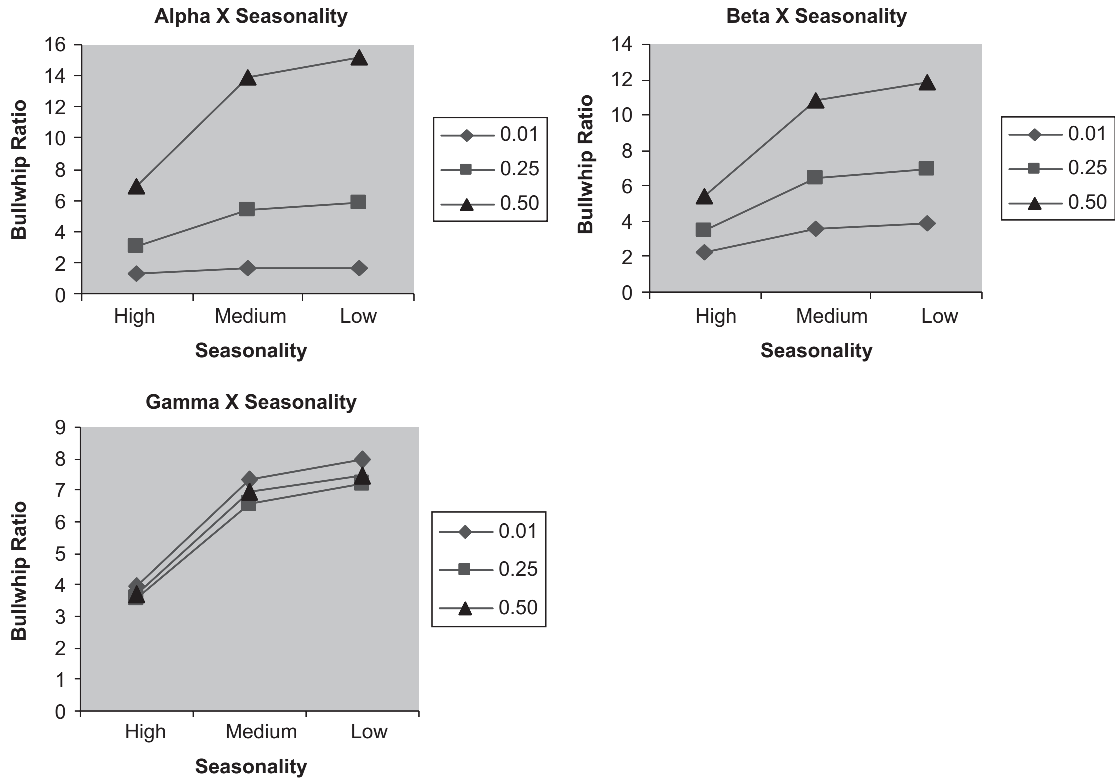

Fig. 4. Interaction effect between smoothing parameters and seasonality.

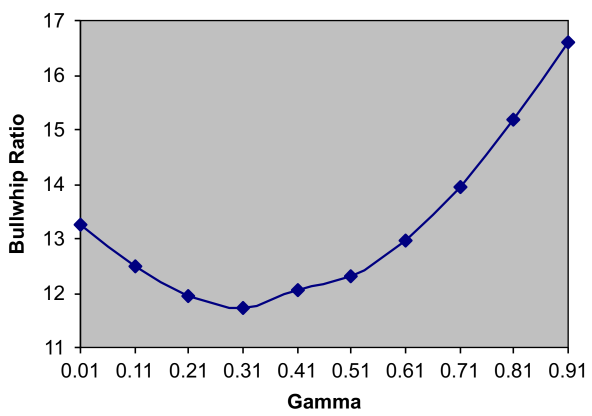

Fig. 5. Bullwhip ratio for different levels of the gamma parameter.

bullwhip effect is compensated by the variability generated by the seasonality. As noted earlier, for some other demand structures, lead time also has a very strong impact on the bullwhip effect for both linear and seasonal demand structures.

It was also found that selection of smoothing parameters (α, β, γ) had a significant impact on the bullwhip ratio in terms of Winter's model for exponential smoothing technique. Of these parameters, the impact of the gamma (γ) parameter on the bullwhip ratio was found to be relatively minor. For a lower bullwhip ratio, choosing relatively lower values for alpha (α) and beta (β) parameters becomes highly important. This is even true for the different levels of lead time and seasonality. Since the relationship between bullwhip effect and gamma parameter is of U-type, the γ parameter should be selected in a way to reduce the bullwhip effect.

The findings of Winter's model parameters to reduce the bullwhip effect have some similarities with those of Winston (1993, p. 1268) for the selection of exponential smoothing parameters for forecast accuracy. Therefore, we may conclude that better forecasting leads to lower bullwhip effect in ECL applications.

This study may further be extended in a way to assess the impact of bullwhip effect on the performance measures of the E-supply chain (e.g., total cost of the members, total chain cost, service level of chain members and service level of the chain). Given the fact that the bullwhip effect has a deteriorating impact on the performance measures of the whole chain, the magnitude of a direct relationship between the bullwhip effect and the performance measures of E-supply chain and its members might be an interesting area for future research. While in practice there are many different forms of on-line customer demands as well as many forecasting techniques to predict these demands, this study focuses on the forecasting of linear seasonal demand through exponential smoothing. Therefore, our findings on seasonality are limited only to the exponential smoothing forecasting, which constitutes the main limitation of this study. Investigation of other techniques of time series analysis for seasonality in E-SCM applications would also prove useful for future research. Similar analyses may be extended to an E-supply chain including more on-retailers, distributors and wholesalers as well as manufacturers with tight capacity limitations in order to observe the impact of seasonality on the bullwhip effect in E-SCM applications.

The most significant managerial implication of this study lies in the need to reduce lead times along the E-supply chain to mitigate the bullwhip effect. While high seasonality would reduce the forecast accuracy, it has a positive influence on the reduction of the bullwhip effect. E-SCM managers are therefore strongly suggested to utilize exponential smoothing by selecting lower values for α and β and a mid-value for γ to keep the bullwhip ratio low, while at the same time to increase forecast accuracy.

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