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ORIGINAL RESEARCH

Assessing the supply chain performance: a causal analysis

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Abstract
Measuring the performance-related factors of a unit within a supply-chain is a challenging problem, mainly because of the complex interactions among the members governed by the supply chain strategy employed. Synergistic use of discrete-event simulation and structural equation modeling allows researchers and practitioners to analyze causal relationships between order-fulfillment characteristics of a supply-chain and retailers' performance metrics. In this study, we model, simulate, and analyze a two-level supply-chain with seasonal linear demand, and using the information therein, develop a causal model to measure the links/relationships among the order-fulfillment factors and the retailer's performance. According to the findings, of all the order-fulfillment characteristics of a supply-chain, the forecast inaccuracy was found to be the most important in mitigating the bullwhip effect. Concerning the total inventory cost and fill-rate as performance indicators of retailers, the desired service level had the highest priority, followed by the lead-time and forecast inaccuracy, respectively. To reduce the total inventory cost, the bullwhip effect seems to have the lowest priority for the retailers, as it does not appear to have a significant impact on the fill rate. Although seasonality (to some extent) influences the retailer's performance, it does not seem to have a significant impact on the ranking of the factors affecting retailers' supply-chain performance; except for the case where the backorder cost is overestimated.

Keywords SCM · Retailers' performance · Service level · Bullwhip effect · Causal analysis

1 Introduction

Retailers are the lowest-level downstream members of a supply chain (SC), directly facing and communicating with the customers. Both market- and consumer behavior-related data, which are invaluable for the whole supply chain, emerge mainly at this level. It should, however, be borne in mind that the consumer markets have been progressively dominated by buyers requiring increasingly more customized goods and services, primarily due to rapid-fire technological advancements and increasing global competition. Regardless of the strategic choice, this crucial role that retailers play as

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part of the whole SC warrants research studies paying closer attention to integral factors related to retailers' performance. However, measuring the performance of a unit in the SC is a highly challenging issue because of the interactions among the members based on the SC strategy employed. The expected role of the members in the chain affects the performance of the unit. For upstream SC members, operation times and yield rates, transportation, and delivery lead times (Simchi-Levi et al. 2003) have a significant impact on their performance. Therefore, a retailer's performance varies with respect to the operational performance of the upstream chain members. In many instances, the customer service levels and inventory levels, as well as the total inventory-related costs, are considered to be among the most critical performance indicators for retailers.

In the midst of the progressively stiffen global competition, facilitating an improved integration among suppliers, manufacturers, distributors, retailers and customers is vital to be able to manage the demand and supply, and hence the profitability (Power et al. 2001; Moberg et al. 2002; Koh et al. 2007). As being one of the most crucial processes directly affecting the performance of the retailers, the order fulfillment process involves all of the SC members. Forecast accuracy, inventory service levels, and order lead times are among the key determinants of this process for retailers. However, making accurate forecasts of customer demand is highly challenging, albeit essential (Ying and Dayong 2005).

As one of the critical antecedents of SC performance, the bullwhip effect has been the subject of a growing research stream and attention recently (Wang and Disney 2016; Zhao et al. 2019). In general, a substantial bullwhip effect is a result of inadequate order policies, high lead times, and fluctuating inventory levels, all of which would lead to low customer service levels for the SC. Thus, the manufacturing and inventory-carrying costs escalate, while the product availability and profit margins shrink (Chopra and Meindl 2001). According to Metters (1997), this may reduce product profitability by up to 40 percent in specific markets.

Despite its importance, there is an apparent scarcity of research focusing on the relationship between the bullwhip effect and the SC performance. To rectify this disparity in our study, we aim to identify the relative importance of a set of tools and operational practices that a retailer may use to improve its SC performance. Therefore, we scrutinize and rank the prominence of several factors related to SC operations for retailers' performance. This study considers the bullwhip effect, forecast inaccuracy, lead-time, seasonality, and desired service level as SC order fulfillment factors, while the retailer's performance is assessed by the total inventory cost and order fill rate. To generate the data to be used for evaluating the performance of a two-stage SC under seasonal linear demand conditions, a simulation model is designed and executed. The retailer's inventory is managed using the order-up-to policy with the exponential smoothing forecasting method. Under different lead times and service level assumptions, and using varying forecasting parameter estimates, the bullwhip effect, fill rate, and total inventory cost of the retailer are measured and recorded. Finally, a causal framework is designed through a structural equation model (SEM) to investigate the hypothesized relations between the SCM-related variables and the retailer's performance—which is measured by the total inventory cost and order fill rate.

The remainder of this paper is organized as follows. The next section provides a review of the most relevant prior research literature. Section 3 discusses the details of the simulation model of a two-stage SC. Based on the simulation model results and obtained data, Sect. 4 explains the construction, execution, and testing of the SEM.

The summary of the study, along with the concluding remarks, is provided in the final section.

2 Literature review and research framework

Measuring the performance of an SC is itself quite a challenging task, despite it being critical to verify the actualization of the desired targets. In practice, many metrics and models have been developed to identify the success of an SC in terms of timeliness, quality, and cost. The supply chain operations reference model (SCOR) emphasizes the reliability, responsiveness, flexibility, and cost dimensions of an SC in the measurement of its performance. The balanced scorecard, on the other hand, focuses on four critical areas of a chain: finances, customers, processes, and learning and growing. Anand and Grover (2015) suggested different factors as performance indicators of a retail SC and classified them into four main categories: transport optimization, inventory optimization, information technology optimization, and resource optimization. These different perspectives indicate the multi-dimensionality of the performance and the difficulty of representing it with a single metric. In this study, the SCM performance of a retailer is measured by two metrics: the total inventory cost of the retailer and the customer service level measured by the order fill rate.

Recently, most studies have focused on the bullwhip effect used to represent the demand amplification phenomenon (e.g., Chatfield and Pritchard 2013; Tangsucheeva and Prabhu 2013; Ma et al. 2019). In his seminal work on the bullwhip effect, Forrester (1961) showed that the internal system of the firm creates it through its policies, organization structure, and delays in material and information flows. Similarly, Sterman (1989) pointed out the role of misperceptions of feedback loops in the bullwhip effect. Later, through mathematical models, Lee et al. (1997) studied the reasons underlying the bullwhip effect in traditional SCs and identified five major factors, which are demand forecasting, order batching, rationing and shortage gaming, price fluctuations and forward buying, and lead times. Zotteri (2013) also showed that the bullwhip effect could be substantial even for products with stable demand, as retailers are more willing to execute forward buying. More recently, Bray et al. (2019) empirically showed the positive relationship between ration gaming and the bullwhip effect. These previous studies jointly highlighted the significance of order batching decisions with certain service level assumptions, forecast accuracy, and lead times in the explanation of the bullwhip effect. Relying on the previous work, in this study, we consider the bullwhip effect as a surrogate factor formed jointly by other factors.

To mitigate the bullwhip effect, Forrester (1961) proposed three strategies: faster order handling, distributor level elimination, and changing the inventory policy. More recently two strategies to reduce the bullwhip effect have been emphasized extensively by researchers as a method to enhance the operational performance of an SC, which are reducing the lead time (Lee et al. 1997; Devika et al. 2016) and developing collaborative relationships among SC members (Danese 2006; Jeong and Hong 2019). The latter facilitates access to more reliable and up-to-date data, which potentially enhances the accuracy of the demand forecast (Disney and Towill 2003; Sari 2008). Using system dynamic simulation, Barlas and Gunduz (2011) showed that demand- and forecast-sharing strategies among SC members could significantly reduce the bullwhip effect. In another study, through a collective investigating of the relations between the bullwhip effect and lead time and forecasting techniques for traditional and information-sharing SCs, Chen et al. (2000a, b) revealed that the lead time and the parameters of forecasting techniques could have a significant impact on the bullwhip effect. Wan and Evers (2011) have also highlighted the extreme importance of identifying and using the most appropriate forecasting technique towards mitigating the bullwhip effect.

Similarly, Dejonckheere et al. (2003) showed that the bullwhip effect exists in the case of the order-up-to policy, regardless of the forecasting technique used in any possible demand pattern. However, the bullwhip effect becomes significantly smaller with shorter lead times. Therefore, longer lead times and inaccurate demand forecasts both contribute to a more substantial bullwhip effect. Thus, we hypothesize:

H1a The lead time is positively associated with the bullwhip effect.

H1b Forecast inaccuracy is positively associated with the bullwhip effect.

The desired service level denotes the level at which the organization is willing to satisfy the customer demand fully and confidently. Higher service levels require more inventories to be kept in stock so that an unexpected spike in customer demand can be adequately met. It is known to be tough to establish a direct link between the service levels and the bullwhip effect; hence it is not expected that higher service levels will have a significant impact on the order frequency and order size to influence the bullwhip effect. Thus, we expect:

H1c The desired service level has no association with the bullwhip effect.

Shortening the lead-time and increasing the forecast accuracy might be the only practical way for a retailer to reduce the investment in inventories without decreasing the availability of a product (Williams and Waller 2011). Longer lead times challenge to respond to short-term market fluctuations and unforeseen customer demand and increase total inventory cost while decreasing service levels (Sari 2015). Along with poor forecasting performance, there is no choice for a firm but to increase the inventory levels to maintain a specific service level. Otherwise, the number of product inventory shortages will increase, and hence the customer service levels will deteriorate. Both will lead to an increase in total inventory costs. Namely, a forecasting method with better accuracy may substantially reduce inventory costs (Tratar 2015). Based on these discussions, the following multi-part hypotheses are proposed:

H2a The lead time is positively associated with the total inventory cost.

H2b Forecast inaccuracy is positively associated with the total inventory cost.

A higher desired service level forces a retailer to invest more in inventories. Increased inventory levels reduce the flexibility of a retailer to respond timely to a customer requiring newer products and increase the risk of product obsolescence. As a result, inventory costs rise further. Thus, we expect:

H2c The desired service level is positively associated with the total inventory cost.

Despite a plethora of empirical research on mitigating the bullwhip effect, there is limited evidence about the direct relationship between bullwhip effect and inventory costs. Using a system dynamics model of a real-world SC, Torres and Maltz (2010) showed that reducing the bullwhip effect did not guarantee either low costs or low inventory levels in today's highly uncertain market conditions. Their findings suggest that the managers of an SC should also identify the most suitable SC strategy and replenishment rule for their specific business conditions.

However, the factors leading to the bullwhip effect also cause to create either excess or shortage of inventory. Both may be costly for retailers and lead up to the loss of customer goodwill. The information-sharing strategies and collaborative planning and scheduling may enhance the visibility in the SC for better demand predictability. These may not eliminate the bullwhip effect; but, substantially reduce the magnitude of its amplification (Dejonckheere et al. 2004; Croson and Donohue 2006). The lack of coordination on SC increases the total inventory costs (Chopra and Meindl 2001). Metters (1997) states that the bullwhip effect may reduce the profitability of a product by up to 40 percent. Bayraktar et al. (2008) also show that the bullwhip effect raises the average inventory levels and reduces the fill rates. Therefore, we hypothesize:

H2d The bullwhip effect is positively associated with the total inventory cost.

As a measure of responsiveness, the fill rate indicates the percentage of the orders that are fulfilled on time. Long lead times and inaccurate demand forecast values make a precise prediction of the inventory levels difficult, and then the accuracy of order sizes deteriorates. As a result, the customer demand may not be satisfied by the available inventory, the shortage occurs, and the customer order is not fulfilled properly. Longer lead times and inaccurate forecasting make order fulfillment difficult and inevitably affect the fill rates negatively (Sari 2015). If the system is designed to set for high service levels to cope with any instability, the level of safety inventory should be increased to compensate for this volatility. Hence, the fill rate of the retailer will be high, albeit costly.

Similarly, the bullwhip effect also increases the instability in the order fulfillment process. Considering the difficulty of doing business under unstable environments, the retailers fail to fulfill the customer orders accurately, and their fill rates get worse because of the bullwhip effect. Therefore, the following multi-part hypotheses are developed:

H3a The lead time is negatively associated with the fill rate.

H3b Forecast inaccuracy is negatively associated with the fill rate.

H3c The desired service level is positively associated with the fill rate.

H3d The bullwhip effect is negatively associated with the fill rate.

Seasonality makes demand prediction challenging and strengthens the effect of lead times. In general, customer service levels are expected to worsen under severe seasonality. To cope with seasonality while maintaining a high level of service, retailers need to keep more inventories on hand, and this results in even higher total inventory costs. In terms of the bullwhip effect, however, the situation depends on how much the order variability will increase in contrast to the variability in demand caused by seasonality. Bayraktar et al. (2008) showed that seasonality might diminish the bullwhip effect. Nagaraja et al. (2015) measured the bullwhip effect under seasonal demand conditions. They also found that shortening the lead-time related to the seasonal lag value can substantially reduce the bullwhip effect. Thus, seasonality invokes many relations used in this study, as shown in Fig. 3. Concerning these complex characteristics of seasonality, we hypothesize:

H4a Seasonality has a differential impact on the path coefficients of the research model for the total inventory cost.

H4b Seasonality has a differential impact on the path coefficients of the research model for the fill rate.

From a managerial perspective, it is also important to recognize the relative importance of order fulfillment factors on SC performance indicators, so that managers may decide to enforce the most effective strategy. To exemplify, Sari (2015) investigated the relative importance of several factors on the SC performance and concluded that the shortening lead-times was the most powerful strategy to reduce total SC cost, while error-free inventory records were found to be the most significant factor for the customer service levels. However, in another study, Mackelprang and Malhotra (2015) found no relationship between the bullwhip effect and the firm's operating margins, a finding which is contrary to the general belief that bullwhip effect results in decreased firm profitability. They also added that this relationship was far more complicated. In a more recent study based on an extensive cross-sectional firm-level data, Baron et al. (2018) also showed no significant statistical or economic relations between bullwhip effect and accounting/financial measures of profitability.

3 System simulation model of a retailer's supply chain

This study concentrates on the relationship between a supplier and a retailer, which represents two consecutive stages in a supply network, as shown in Fig. 1. The supplier delivers a single product to the retailer that satisfies the demand of the customers in the marketplace.

At the beginning of each time interval (t), the retailer receives the delivery of the product from the supplier, which was ordered at time $t–L$ (lead time). Meanwhile, the actual customer demand (D_t) emerges in the marketplace. It is assumed that the product demand

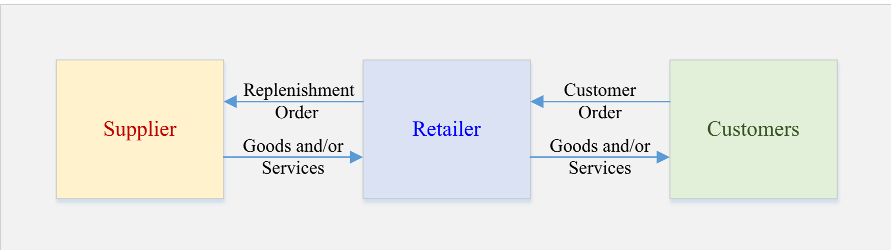

Fig. 1 Simulated supply chain model

in the market follows a seasonally distributed linear demand structure. The retailer satisfies backorders (if they exist) and the current customer demand from existent stocks. Any unsatisfied customer demand is back-ordered. At the end of each time interval, the retailer forecasts the demand for future periods ($\hat{D}_t^{L+1}$) from the historical data using Winter's method (Abraham and Ledolter 1983). Alpha (α), beta (β) and gamma (γ) represent the three exponential smoothing parameters to update the level, trend, and seasonal components of the demand, respectively. According to this demand forecast, the retailer may decide the size of the order to place from the supplier according to its inventory control policy. In this study, we assume that the retailer manages its inventory with an "order-up-to policy" in which the order-up-to point (S_t) is predicted from the actual demand, similar to Chen et al. (2000a) and Sucky (2009). Then, the retailer places its order considering the difference between the order-up-to points in two consecutive periods and the demand in the previous period, as shown in Eq. (1).

$$\begin{aligned} S_t &= \hat{D}_t^{L+1} + z\hat{\sigma}_t^{L+1} \\ Q_t &= S_t - S_{t-1} + D_{t-1} \end{aligned} \tag{1}$$

where $\hat{D}_t^{L+1}$ represents the demand estimate over the lead time and review period of 1, $\hat{\sigma}_t^{L+1}$ is an estimate of the standard deviation of the $L+1$ period forecast error and z is a safety factor chosen to fulfill the desired service level (Chen et al. 2000b).

Similar to earlier studies (Chen et al. 2000a, b; Aviv 2002), this study assumes that there is no partial delivery, and the lead times are deterministic. It is also assumed that the supplier has an infinite supply capacity so that a fixed lead time (L) is necessary for the supplier to fulfill the retailer's order. However, in practice, when a retailer's order exceeds the supplier's capacity, either the lead time is extended, or the order is cut off. Both cases will then reduce the order fulfillment rate and increase the bullwhip effect.

3.1 Demand generation in the simulation model

The study assumes a seasonal linear market demand for the retailer and simulates it as multiplicative time series using Eq. (2). Zhao et al. (2002a) used a comparable form for the additive time series:

$$D_t = (base + slope \times \mathrm{t}) \times \left(1 + \frac{\sin\left(\frac{2\Pi}{52} \times \mathrm{t}\right)}{\mathrm{season}}\right) \times \left(1 + \frac{\mathrm{snormal()}}{noise}\right) \tag{2}$$

D_t denotes the demand in week t. *base* and *slope* represent linear demand parameters with the values of 1000 and 3, respectively. The *season* is a parameter to control the maximum fluctuation level in seasonality. The values of 20, 5 and 2 are assigned to *season* in Eq. (2) to generate up to ±5 percent (*low*), ±20 percent (*medium*), and ±50 percent (*high*) seasonality, respectively. snormal() is a random number with a standard normal distribution between 0 and 1. *Noise* is a parameter to control the level of the error term and is selected as 4 for the model.

3.2 Levels of contextual factors used in the simulation model

In the presence of both seasonality and a linear trend in the demand model, it is assumed that the retailer will use Winter's (triple exponential smoothing) method to forecast future customer demand over the lead time using the historical demand data generated by the simulation model. The three forecasting parameters of Winter's method refer to the level (α), trend (β) and seasonality (γ) components of the demand data. Abiding by Winston's (1993, p. 1268) recommendation, the values of alpha (α) and beta (β) are chosen as 0.01, 0.25, and 0.5. Similarly, the levels of gamma (γ) are set according to Bayraktar et al. (2008). Based on the selection of α, β, and γ, demand forecast inaccuracy is measured by the mean absolute percentage error (MAPE) between the actual demand and the forecasted value. The lead time is fixed as 1, 3, and 5 weeks at 3 levels. The service level is also set at three different rates: 0.90, 0.95, and 0.99.

Through the 4 contextual factors above (namely seasonality, forecasting inaccuracy with 3 parameters, lead time and service level) at 3 different levels each, the simulation model is capable of generating data for a total of $3^6 = 729$ different scenarios. From this experimental set-up, the total cost of inventory and fill rate of the retailer, as well as the bullwhip effect, are computed as performance indicators. The total inventory cost is the sum of the inventory holding cost and backorder cost of the retailer. It should, however, be noted that there is no consensus in the literature about the relationship between unit holding (C_h) and backorder (C_b) costs due to different product and market conditions. To exemplify, in their study Zhao et al. (2002b) assumed the ratio of C_b/C_h to be 50, while Zhao et al. (2002a) and Sari (2007) allocated 10 and 20 to the ratio of C_b/C_h, respectively. Nevertheless, the ratio of $C_b/(C_b + C_h)$ implies the desired service level for order-up-to systems in the literature (Nahmias 2005). Initially, C_h was selected as \$5.00 per week, and then C_b was calculated from the equation, $C_b/(C_b + C_h)$, to be consistent with the desired service rate defined previously. In this study, the fill rate is adapted to measure the service level performance of retailers, although there are many different definitions of service performance (Nahmias 2005). The bullwhip effect, as a conceptualization of demand amplification among the SC stages, is assessed by the bullwhip ratio, which indicates the ratio of the variance of the orders placed to the variance of the demand observed by the retailer:

$$Bullwhip\,Ratio = Var(Order)/Var(Demand).$$

Order variance is a measure of variation stemming from forecast inaccuracy, ordering policy and batch sizes used by the retailer, and lead times in the model.

3.3 Verification and validation of the simulation model

The two-stage SC shown in Fig. 1, the operational processes of which are explained in the earlier subsections, are simulated to determine the effects of several contextual factors on the total inventory cost and fill rate of a retailer. Figure 2 shows the simulation logic of a two-stage SC in a flowchart. For verifying the logic of flow, the entire model is partitioned into four parts: the demand generation process, forecasting process, inventory level calculations, and collection of output statistics. Each section is then debugged individually to check whether the results match the manual solution sets. Then the overall simulation model is traced for integrity, and the outputs are verified with the manually computed results.

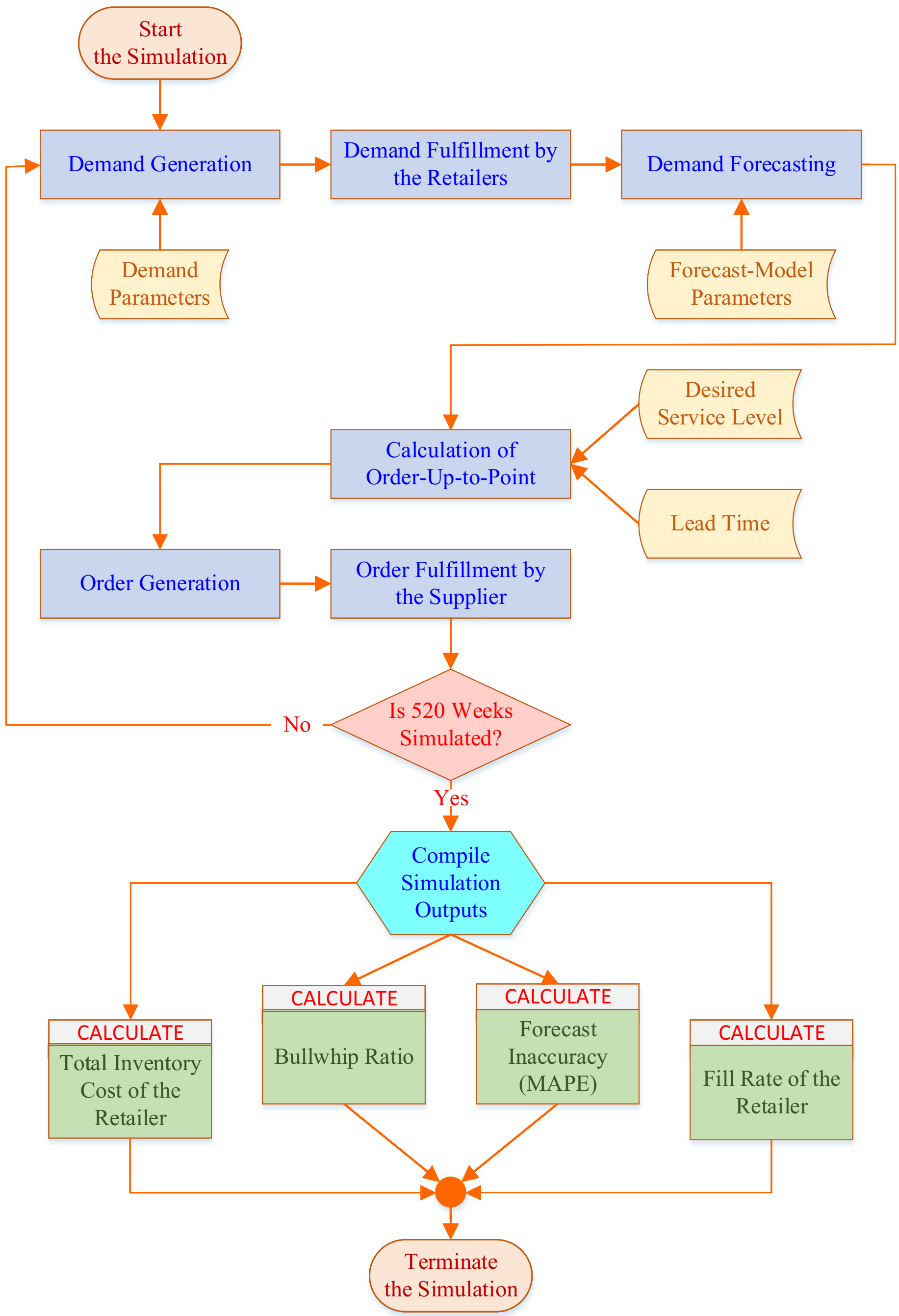

Fig. 2 Flowchart of the simulation model

To validate the simulation outputs, we plot the demand generated by the simulation model on a scatter diagram so that the demand function in Eq. (2) is confirmed. This validation assures that the intended market demand patterns with different seasonality are generated appropriately in the simulation model. The SC model above is simulated for 520 weeks. The first 156 weeks are later removed from the output analysis to eliminate the warm-up period effect, but the initial parameters of the forecasting model are estimated from these initial data. Therefore, the remaining 364 weeks (from week 157 to week 520) are used in the analysis. Besides, each scenario is replicated 20 times to reduce the variance for the statistical significance of the analysis (Banks et al. 1996; Law 2007).

A sensitivity analysis is also conducted on the linear demand model by altering the values of the *base*, *trend,* and *noise* to generate increasing and decreasing demand patterns. It is found that the variation in the demand parameters has no significant impact on our findings. Hence, only the model with increasing demand is selected to explain the rest of the analysis.

4 Results and discussion

The extent of the variations in the bullwhip ratio, total inventory cost and fill rate with respect to a set of variables such as the lead time, forecast inaccuracy and service levels under different seasonality conditions are generated through the simulation model, and the descriptive results are shown in Table 1. According to these descriptive statistics, the bullwhip ratio and total cost increase, but the fill rate fall while the lead time rises incrementally. When the desired service level is increased, both the total cost and the fill rate increase, but the bullwhip ratio does not seem to be very responsive to the changes in the desired service level. On the other hand, increased seasonality diminishes the bullwhip ratio and the fill rate, but the total cost increases, a finding that is also in line with those of Cachon et al. (2007) and Bayraktar et al. (2008).

In this study, an SEM with AMOS is used to test the hypotheses aforementioned. The details of this analysis are explained in the following subsections.

4.1 Structural equation model

For a comprehensive statistical analysis of the results, SEM with a set of structural equations is found to be superior to more conventional statistical tools, such as multiple regression analysis. Through SEM, it is also possible to examine theory and measures simultaneously. The maximum likelihood (ML)-based covariance structure analysis technique (Joreskog 1970; Bollen 1989; Ridgon 1998) is often used for SEM analysis, which is known to be the most prominent technique to date. The objective of covariance-based SEM analysis is to illustrate that the whole set of paths as identified in the model is meaningful and that the operationalization of the theory is substantiated and confirmed by the sample data (Fornell and Bookstein 1982; Hair et al. 2006). Based on the current SCM research and the set of hypotheses developed in the earlier section, a conceptual representation of the relations among the variables is presented in Fig. 3 to consider for the SEM.

To analyze the relationships among the multiple variables in Fig. 3, the links between the SC order fulfillment factors such as the lead times, forecast inaccuracy, desired service levels and bullwhip ratio, and the retailer's performance indicators as assessed by the fill rate and total inventory cost are established. One SEM for each of the retailer's

Table 1 Descriptive statistics of the simulation output

Factors	Seasonality	Bullwhip ratio		Total cost		Fill rate (%)	
		Mean	S.E.	Mean	S.E.	Mean	S.E.
Lead time							
1	Low	3.70	0.05	5,233,745	57,465	96.84	0.05
	Moderate	3.29	0.04	5,358,701	60,893	96.79	0.05
	High	2.24	0.02	6,061,804	78,141	96.46	0.05
3	Low	7.74	0.16	9,998,366	160,877	94.07	0.10
	Moderate	6.75	0.13	10,198,628	164,244	93.99	0.09
	High	4.12	0.07	11,261,855	186,449	93.53	0.09
5	Low	13.36	0.30	13,795,334	231,794	92.83	0.12
	Moderate	11.60	0.26	14,087,807	235,387	92.71	0.12
	High	6.79	0.14	15,405,406	256,924	92.16	0.11
Forecast inaccuracy							
Low	Low	1.56	0.04	5,041,232	138,824	97.20	0.14
	Moderate	1.47	0.03	5,231,185	153,335	97.08	0.12
	High	1.25	0.02	6,032,731	209,410	96.64	0.12
Medium	Low	7.50	0.12	9,442,721	111,155	94.57	0.06
	Moderate	6.54	0.10	9,667,442	114,391	94.48	0.06
	High	4.00	0.06	10,716,775	129,115	94.02	0.06
High	Low	16.38	0.55	13,197,556	429,283	93.59	0.21
	Moderate	14.31	0.48	13,277,571	425,673	93.59	0.22
	High	8.35	0.27	14,247,370	437,654	93.24	0.22
Desired service level							
90%	Low	8.26	0.22	6,191,008	72,515	92.03	0.10
	Moderate	7.22	0.19	6,223,880	72,755	91.99	0.10
	High	4.37	0.11	6,442,374	74,369	91.71	0.10
95%	Low	8.25	0.22	7,967,717	97,978	94.41	0.09
	Moderate	7.20	0.19	8,048,931	98,278	94.33	0.09
	High	4.38	0.11	8,527,324	100,164	93.87	0.09
99%	Low	8.27	0.22	14,868,720	254,615	97.31	0.07
	Moderate	7.22	0.19	15,372,325	256,525	97.18	0.06
	High	4.39	0.11	17,759,367	271,257	96.57	0.06
Bullwhip ratio							
Low	Low	–	–	5,872,186	127,734	96.65	0.14
	Moderate	–	–	6,383,231	126,943	96.38	0.12
	High	–	–	8,284,197	178,849	95.24	0.12
Medium	Low	–	–	7,758,265	129,882	95.25	0.06
	Moderate	–	–	8,303,965	141,151	94.91	0.06
	High	–	–	10,738,185	161,894	93.72	0.06
High	Low	–	–	14,738,555	205,547	92.40	0.21
	Moderate	–	–	15,493,360	224,788	92.20	0.22
	High	–	–	17,608,129	337,649	92.53	0.22

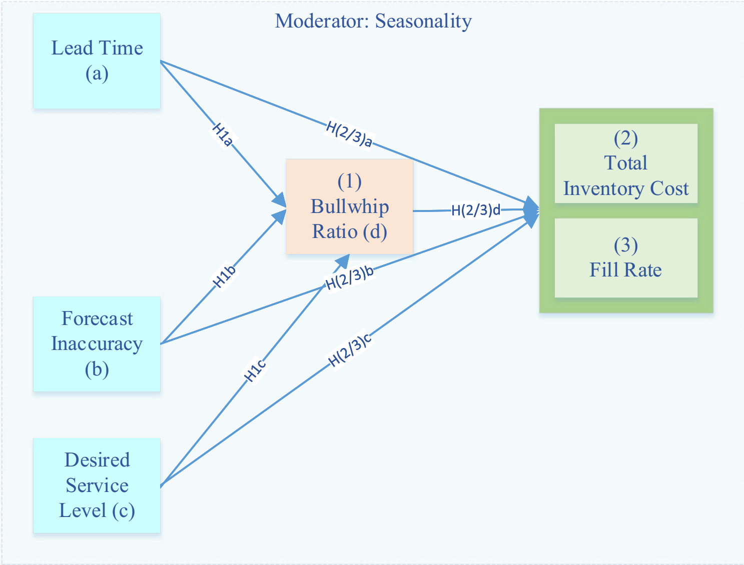

Fig. 3 Research model

Table 2 The goodness of fit statistics for total inventory cost models

Model	χ^2	*p* value	GFI	AGFI	TLI	CFI	RMR	RMSEA
Base model	0.015	0.903	0.980	0.970	0.990	0.990	0.0004	0.0003
Low seasonality model	0.002	0.961	0.990	0.970	0.990	0.990	0.0002	0.0003
Moderate seasonality model	0.004	0.952	1.000	0.980	0.990	0.990	0.0000	0.0002
High seasonality model	0.072	0.789	0.990	0.970	0.990	0.990	0.0002	0.0003

performance indicators, namely the total inventory cost and fill rate, is developed and tested under different seasonality assumptions (i.e., low, moderate and high seasonal settings).

For model specification quality, the path model illustrated in Fig. 3 is tested with the data generated from the multiple simulation runs. In different seasonality settings, the goodness-of-fit statistics for the model using the retailer's total inventory cost as a dependent variable are shown in Table 2, in which the base model represents all the seasonal data sets.

In all the SEM models for measuring the retailer's total cost in Table 2, the significance levels of the χ^2 test statistics are all above 0.79, exceeding the minimum threshold value of 0.05. These indicate that the models are correctly specified. The goodness-of-fit index (GFI) values are close to 1 and acknowledged as a good measure of an adequate model fit (Hair et al. 2006). The values of the adjusted goodness-of-fit index (AGFI) are more than the recommended benchmark value of 0.80; thus, they are considered as a good sign of an adequate model fit (Hair et al. 2006). In these models the root mean square residual (RMS) and root mean square error of approximation (RMSEA) values are less than 0.0004 and 0.0003, respectively, indicating a perfect fit (Schumacker and Lomax 1996). In terms of the goodness-of-fit indices, we need to check two more indices, the Tucker–Lewis index (TLI)

Table 3 Standardized regression weights for causal links

Causal links[§]	Base model	Seasonality		
		Low (±5%)	Moderate (±20%)	High (±50%)
(a) Bullwhip ratio				
Lead time → bullwhip ratio	0.364*	0.366*	0.370*	0.390*
Forecast inaccuracy → bullwhip ratio	0.523*	0.539*	0.539*	0.538*
Desired service level → bullwhip ratio	0.001	0.001	0.000	0.003
(b) Total inventory cost				
Bullwhip ratio → total inventory cost	0.194*	0.251*	0.241*	0.218*
Lead time → total inventory cost	0.514*	0.508*	0.506*	0.479*
Forecast inaccuracy → total inventory cost	0.267*	0.256*	0.246*	0.224*
Desired service level → total inventory cost	0.546*	0.515*	0.532*	0.595*
(c) Fill rate				
Bullwhip ratio → fill rate	0.025	−0.009	0.004	0.025
Lead time → fill rate	−0.429*	−0.403*	−0.416*	−0.451*
Forecast inaccuracy → fill rate	−0.294*	−0.285*	−0.284*	−0.287*
Desired service level → fill rate	0.499*	0.513*	0.506*	0.480*

[§]In (.) transformation is used for all variables

*$p < 0.01$

and the comparative fit index (CFI). The value of both indexes is 0.99 in all four models, which is very close to 1. Relying on these model fit criteria, the path model adequately fits the data. Predictors of the SEM model are set in the simulation runs in a way that the correlations among them are zero. Therefore, multi-collinearity is not an issue for SEM at all. A similar analysis for the SEMs to measure the retailer's fill rates is also conducted, but the results are not shown here. According to the aforementioned goodness-of-fit statistics, these SEMs also indicate excellent model fits.

In Table 3a–c, the results of the ML method to derive parameter estimates for the SEMs are shown in terms of the standardized regression weights.

In Table 3a strong support is found for Hypotheses H1a and H1b that the lead time and forecast inaccuracy have positive and significant associations with the bullwhip ratio ($\beta = 0.364$ and $\beta = 0.523$ at $p < 0.01$). Poor forecast accuracy and longer lead times cause exponential increases in the bullwhip ratio. The finding that lower lead times help to reduce the bullwhip ratio tends to corroborate the results of earlier studies (Chen et al. 2000a, b; Zhang 2004; Luong and Phien 2007; Bayraktar et al. 2008). Similarly, Table 1 reveals that, when the level of forecast inaccuracy is low, the bullwhip ratio is between 1.25 and 1.56; however, when the level of forecast inaccuracy is high, it is in a range from 8.35 to 16.38. The finding that a more accurate demand forecast reduces the bullwhip ratio tends to confirm the results of earlier studies (Chen et al. 2000a, b; Bayraktar et al. 2008; Wright and Yuan 2008; Wan and Evers 2011). Therefore, a retailer, to avoid the bullwhip effect, should emphasize greater demand forecast accuracy then lead times.

No significant association, however, is found between the bullwhip ratio and the desired service levels, thus supporting Hypothesis 1c ($\beta = 0.001$, $p > 0.1$). The same finding is also held under different seasonality conditions, as indicated in Table 3a. This finding suggests that the retailer's service level target has no impact on the bullwhip effect even under different seasonality settings. For example, Table 1 shows that the bullwhip ratio under moderate seasonality is 7.22, 7.20, and 7.22 for the 90, 95, and 99 percent desired service levels for the retailer, respectively. As a result, the link between the desired service level and the bullwhip ratio is not considered in the rest of the analysis.

Parallel analysis is also conducted to test the level of deviation in the total inventory cost for SC order fulfillment factors. Based on the SEM results in Table 3b, the lead time is found to influence the total inventory cost of retailers significantly, thus confirming Hypothesis 2a ($\beta = 0.514$, $p < 0.01$). For retailers who intend to diminish the total inventory cost, the long lead times, along with the desired service level, are likely to constitute the most critical area on which to concentrate. An additional statistically significant result is that increased forecast inaccuracy leads to higher total inventory costs for retailers, which supports Hypothesis 2b ($\beta = 0.267$, $p < 0.01$). Indeed, the usage of an appropriate demand forecasting method with expertly chosen parameters enables the enhancement of the forecasting accuracy as well as the reduction of the total inventory cost, which is in line with the previous studies (Metters 1997; Zhao et al. 2002b). Consistent with our expectations, Table 3b indicates that higher levels of customer service are positively related to the total inventory cost, supporting Hypothesis 2c ($\beta = 0.546$; $p < 0.01$) very strongly. Furthermore, a positive association is noted between the total inventory cost of the retailer and the bullwhip effect, thus supporting Hypothesis 2d ($\beta = 0.194$; $p < 0.01$). This finding confirms those of previous studies (Metters 1997; Zhao et al. 2002b).

Hypotheses 3a, 3b, and 3c, related to the lead time, forecast inaccuracy and desired service level, are all supported with statistically significant β values of -0.429, -0.294 and 0.499 for the base model, respectively, as depicted in Table 3c for the fill rate. The desired service level is the most critical factor to influence the fill rate with the highest standardized regression weight in Table 3c. High forecast inaccuracy, as well as long lead times, negatively affect the fill rate, as they are anticipated.

Contrary to our expectation stated in Hypothesis 3d, there is no statistically significant relationship between the bullwhip ratio and the fill rate ($\beta = 0.025$; $p > 0.01$). Further, this finding is confirmed by the separate analysis performed under low, moderate and high seasonality of the demand, as revealed in Table 3c, and is in line with the earlier research (Zhao et al. 2002b).

A multiple-group analysis is also applied to each of the performance indicators, namely the total inventory cost and fill rate, to assess the moderating effect of seasonality on the structural models (Bryne 2001). Two structural models for each performance indicator are created to compare the Chi square statistics. The first model is an unconstrained model in which the path coefficients are allowed to vary across the seasonality subgroups. The second model is a constrained model in which the path coefficients are constrained to be equal across the different seasonality subgroups. The differences between the two Chi square values of the constrained and unconstrained models are found to be 231.26 and 97.57 for the total inventory cost and fill rate, respectively, which are statistically significant ($p < 0.001$). These results support Hypotheses 4a and 4b, indicating that seasonality as a moderator has a significant differential impact on the path coefficients for each performance indicator.

When dealing with a cross-sectional data set, bootstrapping allows us to assess the validity of our results even when their statistical properties are not well known (Bryne 2001; Lattin et al. 2003). To measure the effects of the following factors, namely the lead time, desired service level and forecast inaccuracy, on the total inventory cost and fill rate, 90 percent bootstrapping confidence intervals with lower and upper limits are generated from the unstandardized regression weights of the models stated in Table 3a–c and shown in Tables 4, 5 and 6.

Table 4 Percentage changes in the bullwhip ratio[§]

Causal links[§§]	Increment (%)	Seasonality					
		Low (± 5%)		Moderate (± 20%)		High (± 50%)	
		L.L.	*U.L.*	*L.L.*	*U.L.*	*L.L.*	*U.L.*
Lead time	100	43.2	48.5	42.1	47.0	36.6	40.5
	50	23.4	26.0	22.8	25.3	20.0	22.0
Forecast inaccuracy	100	1453.0	2125.4	1350.0	1921.0	844.8	1147.5
	50	397.5	514.0	377.9	480.4	272.0	337.7

[§]$(1 + \text{Increment})^{\beta} - 1$, where β represents the unstandardized regression weight associated with a 90% lower limit (U.L.) and upper limit (U.L.) of bootstrapping confidence interval of the causal link in Table 3a

[§§]In () transformation is used for all variables

Table 5 Percentage changes in the total inventory cost[§]

Causal links[§§]	Increment (%)	Seasonality					
		Low (± 5%)		Moderate (± 20%)		High (± 50%)	
		L.L.	*U.L.*	*L.L.*	*U.L.*	*L.L.*	*U.L.*
Bullwhip ratio	100	10.5	12.3	10.5	12.3	11.4	13.5
	50	6.0	7.0	6.0	7.0	6.5	7.7
Lead time	100	36.8	38.8	36.7	39.0	35.9	38.1
	50	20.1	21.1	20.1	21.2	19.6	20.8
Forecast inaccuracy	100	118.3	148.8	113.8	141.9	105.5	131.0
	50	57.9	70.4	56.0	67.7	52.4	63.2
Desired service level	5	47.0	49.2	49.3	51.8	59.2	61.7
	1	8.2	8.5	8.5	8.9	9.9	10.3

[§]$(1 + \text{Increment})^{\beta}$-1 where β the unstandardized regression weight associated with 90% lower limit (U.L.) and upper limit (U.L.) of bootstrapping confidence interval of the causal link in Table 3b

[§§]In () transformation is used for all variables

4.2 Factors affecting the bullwhip effect

Table 4 indicates the effects of the lead time and forecast inaccuracy on the bullwhip ratio. Any delay in the lead time equivalent to its size tends to increase the bullwhip ratio by as little as 36.6 percent in high seasonality and as much as 48.5 percent in low seasonality. However, a similar deterioration rate in the forecast inaccuracy amplifies the bullwhip ratio between 8.4 times in high seasonality and 21.3 times in low seasonality. As shown in these examples, the impact of seasonality on the bullwhip effect is not harmful, as highlighted earlier by Cachon et al. (2007) and Bayraktar et al. (2008), and in fact, seasonality in the market demand tends to decrease the bullwhip effect. Therefore, retailers facing a highly seasonal customer demand focus less on the bullwhip ratio. Both lead time and forecast inaccuracy under high seasonality have a relatively weaker influence on the bullwhip ratio. For example, forecast inaccuracy that worsens twice increases the bullwhip ratio at least 14.5 times under low seasonality, while it amplifies it at most 11.5 times with high seasonality.

Table 6 Percentage changes in the fill rate[§]

Causal links[§§]	Increment (%)	Seasonality					
		Low (±5%)		Moderate (±20%)		High (±50%)	
		L.L.	*U.L.*	*L.L.*	*U.L.*	*L.L.*	*U.L.*
Bullwhip ratio	100	–	–	–	–	–	–
	50	–	–	–	–	–	–
Lead time	100	−1.9	−1.7	−2.0	−1.8	−2.1	−1.9
	50	−1.1	−1.0	−1.2	−1.0	−1.2	−1.1
Forecast inaccuracy	100	−7.7	−5.6	−7.7	−5.6	−7.7	−5.8
	50	−4.6	−3.3	−4.6	−3.3	−4.6	−3.4
Desired service level	5	2.8	3.0	2.8	3.0	2.6	2.8
	1	0.6	0.6	0.6	0.6	0.5	0.6

[§] $(1+\text{Increment})^{\beta}-1$ where β represents the unstandardized regression weight associated with 90% lower limit (U.L.) and upper limit (U.L.) of bootstrapping confidence interval of the causal link in Table 3c

[§§] ln () transformation is used for all variables

4.3 Factors affecting the total inventory cost of the retailer

Table 5 illustrates the level of change in the total inventory cost associated with the factors affecting retailers in the SC, including the bullwhip ratio, forecast inaccuracy, lead time, and desired service level. When the bullwhip ratio is doubled, the total inventory cost increases by between 10.5 and 13.5 percent. In the case of the lead time, a similar increment escalates the total inventory cost to a level of 35.9 to 39.0 percent more under various seasonality conditions. When forecast inaccuracy worsens twice, the total inventory cost increases by at least 105.5 and at most 148.8 percent under high and low seasonality, respectively. A 1 percent change in the desired service level increases the total inventory cost by 8.2 to 10.3 percent under the given cost parameters. On the other hand, as seasonality increases, the percentage change in the total inventory cost decreases slightly for an increment in forecast inaccuracy. However, a rise in the desired service level tends to increase the percentage change in the total inventory cost slightly more under high seasonality.

4.4 Factors affecting the fill rate of the retailer

Table 6 shows that possible changes may occur in the fill rate in response to the increments to the SC-related order fulfillment factors. As noted earlier, any change in the bullwhip ratio has no significant effect on the fill rate under any seasonality condition. Twice as long lead time and twice as bad a forecast inaccuracy level are likely to reduce the fill rate by up to 2.1 and 7.7 percent, respectively. A 1 percent increment in the desired service level may help to raise the fill rate at most by 0.6 percent. It is noteworthy that seasonality appears to exert a limited impact on the fill rate.

4.5 Effects of cost parameters on the total inventory cost of the retailer

Because of the difficulty in setting the correct backorder cost in inventory cost calculations, it is common to guess the value of the backorder cost intuitively in practice. To investigate the sensitivity of our results to the inventory cost parameters used in the simulation model, we set the backorder cost (C_b) to \$10.00 ($C_b/C_h = 2$) and \$500.00 ($C_b/C_h = 100$) to underestimate and overestimate the backorder costs, respectively. These two figures are selected divergent to the desired service levels implied by the management. Then, an SEM is developed for each case, and the results are shown in Table 7a, b. A multiple-group analysis to assess the effect of seasonality in each total inventory cost model indicates that seasonality has significant influence (the differences between the Chi square values of the seasonality subgroups are 330.44 and 184.48, respectively, $p < 0.001$) even under different inventory cost assumptions.

In the total inventory cost models, the most notable change occurs in the regression weight of the desired service level. While the backorder cost is appropriately harmonized with the associated desired service level, the desired service level has a powerful positive impact on the total inventory cost ($\beta = 0.546$; $p < 0.01$ in Table 3b). Its effect becomes even stronger under severe seasonality. If the backorder cost is underestimated by the management compared with the desired service level, as in the case of $C_b/C_h = 2$, the desired service level and the total inventory cost increase respectively, but quite naturally the total inventory cost is underestimated. In the case of overestimation of the backorder cost ($C_b/C_h = 100$), there is still a strong relationship between the desired service level and the total inventory cost ($\beta = -0.517$, $p < 0.01$), but its sign is negative, indicating that the increased service level leads the total inventory cost to decrease. This might be explained by the fact that either the desired service level is set too low or the backorder cost is set too high, and then the shortage of inventory is penalized very harshly.

Table 7 Standardized regression weights for total inventory cost

Causal links[§]	Base model	Seasonality		
		Low (±5%)	Moderate (±20%)	High (±50%)
*(a) Underestimated shortage cost ($C_b/C_h = 2$)**				
Bullwhip ratio → total inventory cost	0.332	0.370	0.373	0.391
Lead time → total inventory cost	0.630	0.616	0.614	0.598
Forecast inaccuracy → total inventory cost	0.300	0.278	0.274	0.258
Desired service level → total inventory cost	0.243	0.236	0.240	0.254
*(b) Overestimated shortage cost ($C_b/C_h = 100$)**				
Bullwhip ratio → total inventory cost	0.136	0.187	0.178	0.160
Lead time → total inventory cost	0.498	0.466	0.480	0.508
Forecast inaccuracy → total inventory cost	0.264	0.244	0.239	0.242
Desired service level → total inventory cost	−0.517	−0.542	−0.530	−0.482

[§]In (.) transformation is used for all variables

*All coefficients are significant, $p < 0.01$

It is also noteworthy that the weight of the bullwhip ratio decreases while the overestimation of the backorder cost increases. Intuitively, the bullwhip ratio has less influence on, and importance to the total inventory cost when the management overestimates the backorder cost compared with the desired service level.

4.6 The relative importance of the factors affecting the retailer's supply chain performance

Based on the standardized regression weights shown in Tables 3a–c, 7a, b, the most influential factors affecting the retailer's performance are identified and listed in Table 8 for each performance indicator. As noted earlier, seasonality as a moderator effect has a particular impact on the retailer's performance, though it is not strong enough to change the ranking of these factors much. In Table 8, the forward (backward) arrows indicate a positive (negative) association between the factor and the performance metric. While the intensity of seasonality increases, up (down) arrows show that the strength of this association also goes up (down).

For the total inventory cost, the desired service level is one of the most critical factors, with a β value of 0.546. The desired service level preserves its importance even if the total inventory cost is overestimated because of the highly evaluated backorder cost ($\beta = -0.517$). The negative sign in the latter case indicates the overestimation of backorder cost, which means that increasing service levels reduce the total inventory cost. When the total inventory cost is underestimated by setting a low backorder cost, the desired service level is the least important one, since the number of backorders is assessed with an underestimated cost. Under severe seasonality conditions, the importance of the desired service level increases in all the total inventory cost models but the overestimated one. It should be noted that the lead time is the second most crucial factor for the total inventory cost (the most important one for the underestimated total inventory cost). It is surprising to observe that the bullwhip ratio is ranked last for the total inventory cost criteria. If the cost is underestimated, it could be ranked second. The severity of the seasonality reduces the relative importance of the bullwhip ratio further for the total inventory cost and its overestimated versions.

The desired service level is the highest-ranked factor for the fill rate ($\beta = 0.499$). The lead time and forecast inaccuracy with a negative association hold the next-highest ranks, respectively. It is noteworthy that the bullwhip ratio is not a significant factor ($\beta = 0.025$) for the fill rate, which is commonly used in practice.

The factor that has the most significant impact on the bullwhip effect is the forecast inaccuracy, and it has relatively more important than the lead time in mitigating the bullwhip effect.

4.7 The mediating role of the bullwhip effect

As shown in Fig. 3, the bullwhip effect serves as a mediator in the research model between the lead time and the total inventory cost (fill rate) as well as between the forecast inaccuracy and the total inventory cost (fill rate). Figure 4a, b show these relations with standardized regression weights for the total inventory cost and fill rate respectively.

Table 8 The priority of the factors affecting the retailer's supply chain performance[§]

Rank	Total inventory cost			Fill rate	Bullwhip ratio
	Under evaluated ($C_b/C_h = 2$)	Regular evaluation	Over evaluated ($C_b/C_h = 100$)		
1	Lead time (↘)	Desired service level (↗)	Desired service level (↘)	Desired service level (↘)	Forecast inaccuracy (→)
2	Bullwhip ratio (↗)	Lead time (↘)	Lead time (↗)	Lead time (↖)	Lead time (↗)
3	Forecast inaccuracy (↘)	Forecast inaccuracy (↘)	Forecast inaccuracy (→)	Forecast inaccuracy (←)	Desired service level (NS)
4	Desired service level (↗)	Bullwhip ratio (↘)	Bullwhip ratio (↘)	Bullwhip ratio (NS)	

[§] ↗ (↘)—Increasing (decreasing) positive association between the factor and performance indicator, while seasonality increases

↖—Increasing negative association between the factor and performance indicator, while seasonality increases

→ (←)—Stable positive (Negative) association between the factor and performance indicator, while seasonality increases

NS not significant association

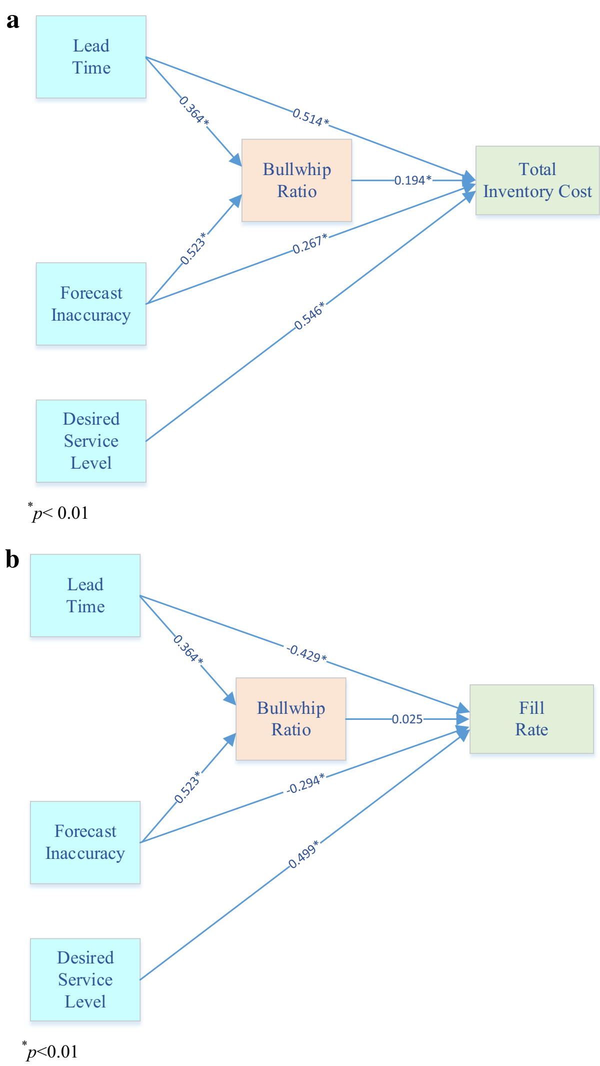

Fig. 4 **a** The role of the bullwhip ratio on total inventory cost (base model). **b** The role of the bullwhip ratio on fill rate (base model)

In the total inventory cost model shown in Fig. 4a, all the regression weights are statistically significant, and the direct effects between the lead time and the total inventory cost and between the forecast inaccuracy and the total inventory cost are much stronger than the indirect effects. Therefore, the bullwhip ratio partially mediates the links between the lead time and the total inventory cost and between the forecast inaccuracy and the total inventory cost.

A similar analysis may be conducted for the fill rate as in Fig. 4b. Since the link between the bullwhip ratio and the fill rate is not statistically significant, it is not possible to establish an indirect link, and there is no mediating role for the bullwhip ratio between the lead time and the fill rate and between the forecast inaccuracy and the fill rate.

As a result of this analysis, it is found that the bullwhip ratio partially mediates the links between lead time and forecast inaccuracy, and the total inventory cost but has no mediation role for the fill rate. Based on the results of our research model, the bullwhip ratio may not be fully capable of representing the SC order fulfillment environment as a surrogate factor, and may not explain itself all variations on the performance indicators of retailers.

5 Conclusions

This study has attempted to identify the relative importance of a set of tools and practices that a retailer may use to improve its SC performance. Therefore, we scrutinized and ranked the relative importance of several SC-related order fulfillment factors in a retailer's performance. These factors were recognized as the bullwhip effect, forecast inaccuracy, lead time, seasonality, and desired service level, while the total inventory cost and fill rate assessed the retailer's performance. A two-level SC with seasonal linear demand was simulated under varying operating conditions to examine the associations between the SC order fulfillment factors and the retailer's performance.

Then a causal model based on an SEM was developed and tested to provide a rigorous analysis of the causal links among the SC-related variables and the retailer's performance. The SEM enabled us to quantify these links. In our analysis, forecast inaccuracy was found to be the most critical factor in mitigating the bullwhip ratio. A 100 percent increment in the forecast errors is likely to increase the bullwhip ratio by up to 2125 percent under different seasonality conditions on the market. Concerning the total inventory cost and fill rate, the desired service level has the highest priority for the retailers, followed by the lead time and forecast inaccuracy. A 1 percent change in the desired service level may increase the total inventory cost by up to 10.3 percent and the fill rate by 0.6 percent. If the lead time delays by 100 percent, the total inventory cost may increase by as much as 39 percent, but it reduces the fill rate by up to 2.1 percent. For the total inventory cost, the bullwhip ratio had the lowest priority for the retailers. When the bullwhip ratio doubles, the total cost may increase by 13.5 percent, but the fill rate is not affected by this amplification significantly. Although seasonality to some extent affects the retailer's performance, it does not have a substantial effect on the ranking of the factors affecting the retailer's SC performance unless the backorder cost is not overestimated.

One of the significant managerial implications of the study is to draw attention to selecting the right service level for retailers. The estimation of the backorder cost in practice is still subjective and left to the judgment and intuition of decision-makers. If it is underestimated, the desired service level will not receive well-deserved treatment from the retailers. Seasonality also strengthens the importance of selecting the right desired service level for the total inventory cost of retailers. Decreasing lead time and increasing forecast accuracy are the next two SC-related factors on which retailers should focus the most. Finally, the bullwhip ratio is the least important factor in improving the total inventory cost and fill rate of retailers unless the backorder cost is not underestimated.

This study uses hypothetical data generated by a simulation model and assumes that decision-makers make rational decisions and uses the most appropriate technics, wherever available. However, this may not be held in practice, and it is the biggest shortcoming of the study. Empirical data sets and practices drawn from the case studies would be quite helpful to enhance our real-life experience of SC practices.

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