



# The impact of information sharing and inventory control coordination on supply chain performances <sup>☆</sup>



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## ARTICLE INFO

### Article history:

Received 16 October 2013

Received in revised form 2 August 2014

Accepted 12 August 2014

Available online 22 August 2014

### Keywords:

Supply chain

Information sharing

Bullwhip effect

Inventory variance

Service level

Simulation

## ABSTRACT

The lack of coordination in supply chains can cause various inefficiencies like bullwhip effect and inventory instability. Extensive researches quantified the value of sharing and forecasting of customer demand, considering that all the supply chain partners can have access to the same information. However, only few studies devoted to identify the value of limited collaboration or information visibility, considering their impact on the overall supply chain performances for local and global service level. This paper attempts to fill this gap by investigating the interaction of collaboration and coordination in a four-echelon supply chain under different scenarios of information sharing level. The results of the simulation study show to what extent the bullwhip effect and the inventory variance increase and amplify when a periodic review order-up-to level policy applies, noting that more benefits generate when coordination starts at downstream echelons. A factorial design confirmed the importance of information sharing and quantified its interactions with inventory control parameters, proving that a poor forecasting and definition of safety stock levels have a significant contribution to the instability across the chain. These results provide useful implications for supply chain managers on how to control and drive supply chain performances.

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## 1. Introduction

Similar to the shape of a cowboy cracking his lash, the bullwhip effect (Fig. 1) is the amplification of the demand variance as information flows across the supply chain, from customer to factory (Chatfield, Kim, Harrison, & Hayya, 2004; Lee, Padmanabhan, & Whang, 1997b). Starting from the most famous experiences at Campbell Soup's (Fisher, Hammond, Obermeyer, & Raman, 1997), HP and Procter & Gamble (Lee, Padmanabhan, & Whang, 1997a), a clothing supply chain (Disney & Towill, 2003a), Glosuch (McCullen & Towill, 2000) till the recent examples of fast moving consumer goods (Zotteri, 2012) and car manufacturing (Klug, 2013), the bullwhip effect continues to show its impact on supply chain performances. Many researchers illustrated the bullwhip dynamics and its negative effects: the amplification of order variance requires a managerial effort that results in a consequent increase of costs to

maintain a target service level (Chatfield et al., 2004) and a further reduction of business performances due to:

- High levels of inventory to face unexpected variations of the demand with a relative increase of stocking costs, as the amount of safety stocks derives from the order variability.
- Low service level to customers for unexpected stock-outs that, in the worst cases, can cause the cancellation of orders and the reduction of actual and future sales.
- Reduction of quality for the necessity to increase production rates to satisfy peaks of demand.
- Increase of costs for rescheduling, updating of production plans and reworking.

Besides the role of misperception of feedback by managers and of operational causes, accurately described starting from the research of Sterman (1989), there is still a substantial need to understand the contribution that coordination and collaboration could give to counteract it in a modern and competitive environment.

According to these considerations, this paper presents the following structure: (1) a literature review in Section 2 provides the motivations and the scope of the research, determining the specific

<sup>☆</sup> This manuscript was processed by Area Editor Mohamad Y. Jaber.

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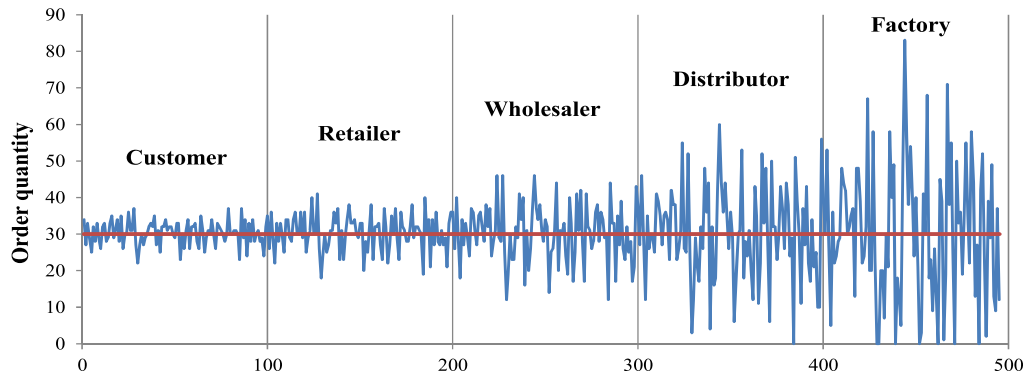


Fig. 1. An example of demand amplification in a linear supply chain.

field of analysis; (2) Section 3 describes the supply chain simulation model and the performance measurement system; (3) Section 4 provides a quantification of the impact of different information sharing levels on supply chain performances; (4) Section 5 shows the interactions of the inventory control parameters on the performances, according to different levels of information sharing; (5) Section 6 gives general insights and implications for managers, and Section 7 summarizes the conclusions.

## 2. Literature review

Forrester (1958) was the first to observe and describe the bullwhip effect, calling it “demand amplification”, determining that it is due to natural system dynamics and delays in supply chain. Reducing the lead-time between echelons and adopting coordination approaches such as vendor-managed inventory, to eliminate decision-making layers and increase visibility on information without distortion, can help to smooth this effect (Disney & Towill, 2003b; Lee et al., 1997b).

Two classes of sources cause the bullwhip effect: behavioral causes (Nienhaus, Ziegenbein, & Schoensleben, 2006; Rong, Shen, & Snyder, 2008; Sterman, 1989) and operational causes (Lee et al., 1997a, 1997b). The first refers to the evidence that decision makers consistently underweight the supply line when making order decisions (Croson & Donohue, 2006) while the second relates to the operational conditions of the replenishment process as for demand signal processing, non-zero lead-times, order batching, price fluctuations, rationing and shortage gaming.

In particular, demand signal processing encompasses the forecasting of future demand and inventory adjustment through applying inventory control policies, proven by Disney and Lambrecht (2008) to be of a significant importance. In this stream of research, many studies attempted to identify the impact on the bullwhip effect of different inventory control policies, evaluating the role of forecasting methods (Barlas & Gunduz, 2011; Chen, Drezner, Ryan, & Simchi-Levi, 2000; Chen, Ryan, & Simchi-Levi, 2000; Dejonckheere, Disney, Lambrecht, & Towill, 2003, 2004; Hosoda & Disney, 2006a, 2006b; Wright & Yuan, 2008; Zhang, 2004), lead-times (Chatfield, 2013; Chatfield et al., 2004; Chen, Drezner, et al., 2000; Chen, Ryan, et al., 2000; Ciancimino, Cannella, Bruccoleri, & Framinan, 2012; Dejonckheere et al., 2003, 2004; Kelepouris, Miliotis, & Pramataris, 2008) and information sharing (Chatfield & Pritchard, 2013; Chatfield et al., 2004; Chen, Drezner, et al., 2000; Dejonckheere et al., 2004; Kelepouris et al., 2008) to give useful insights for supply chain managers on how to handle demand variability amplification. A specific attention is to give to side effects of bullwhip effect, as for inventory stability, especially in multi-echelon supply chains: while the amplification of the demand contributes to the increase of the production and inventory costs, the

variance of the net inventory determines the ability of any single organization to meet a service level in a cost-effective manner (Hussain, Shome, & Lee, 2012; Ma, Wang, Che, Huang, & Xu, 2013). To this extent, most studies focused on the periodic review order-up-to policy because of its popularity (Chatfield & Pritchard, 2013; Dejonckheere et al., 2003; Disney & Lambrecht, 2008; Wright & Yuan, 2008). The order-up-to policy is a common strategy when there is no fixed ordering cost (e.g. in case of visiting agents or framework contracts with suppliers) or both holding and shortage costs are proportional to the volume of the on-hand inventory (Dejonckheere et al., 2003). The important role of this inventory control rule in many supply chains derives from the small set of parameters to set as the only information for its implementation are a forecasting value of demand and a level of safety stock, to determine according to a required service level. Of particular interest, Chen, Drezner, et al. (2000) quantified the bullwhip effect in a two-echelon serial supply chain experiences auto-regressive AR(1) demand process and employs the order-up-to level with the moving average method, and they further extended the results for a multi-echelon supply chain both with and without information sharing. Chen, Ryan, et al. (2000) extended the analysis for a supply chain employs the order-up-to level with the exponential smoothing method. Xu, Dong, and Evers (2001) obtained similar results using the exponential smoothing technique. Chen, Ryan, et al. (2000) showed also that, if the forecasting parameters for both exponential smoothing and moving average methods are set to achieve the same forecasting accuracy, then moving average gives a lower order variance. Dejonckheere et al. (2004) confirmed these results using a control theoretic approach. Chatfield et al. (2004) examined the effects of stochastic lead times, information sharing and quality of information in a periodic review order-up-to level inventory system through a simulation study. They considered three measures to track the supply chain performance, namely, standard deviation of the orders at each echelon, total variance amplification (i.e. bullwhip effect) and stage variance amplification. They concluded that lead-time variability exacerbates variance amplification and that information sharing and information quality are highly significant to handle the propagation of variability. Jakšič and Rusjan (2008), Kelepouris et al. (2008), Wright and Yuan (2008), Hussain et al. (2012), Chatfield (2013) and Chatfield, Hayya, and Cook (2013) conducted similar studies to confirm these findings in more complex configurations of supply chains or different inventory control conditions.

Different mitigation strategies can help to overcome the effect of demand signal processing, from improving the operational efficiency to the use of collaboration approaches in decision making (Campuzano-Bolarín, Mula, & Peidro, 2013; Costantino, Di Gravio, Shaban, & Tronci, 2013a; Costantino, Di Gravio, Shaban, & Tronci, 2013b; Dejonckheere et al., 2004; O'Donnell et al., 2006). In

particular, Holweg, Disney, Holmström, and Småros (2005) classified supply chain collaboration initiatives on inventory replenishment and forecasting dimensions, concluding that any action have to integrate both these areas to reach significant improvements. Interventions that improve, locally or globally, the level of coordination showed their effectiveness in practice (Chatfield et al., 2004; Cho & Lee, 2013; Costantino et al., 2013a, 2013b; Kelepouris et al., 2008; Ye & Wang, 2013).

Most of previous works assumed that all partners use the same forecasting methods and inventory control policy with the same parameters. In addition, they assumed that, if there is collaboration (i.e. information sharing of customer demand), all partners participate. The paper extends these efforts through measuring performances under different levels of information sharing, forecasting parameters and safety stock level at the upstream and downstream echelons of the supply chain. This results in different scenarios of partial collaboration to quantify the effectiveness to what extent the coordination of policies among partners can help in smoothing the bullwhip effect in a multi-echelon supply chain. To allow comparisons with the main cited research, the partners apply a periodic review order-up-to policy with a moving average forecasting method where the amplification of the demand, the inventory variance and the service level are measures of performance, coherently to Kurien and Qureshi (2011) review and Tangen (2004) framework. To this extent and according to the classification of Chatfield (2013), simulation is the most appropriate approach to study supply chain complex dynamics. Similar experiences proved the effectiveness of discrete-event simulation (Tako & Robinson, 2012; Chatfield, 2013; Costantino, Di Gravio, Shaban, & Tronci, 2014a, 2014b, 2014c; Costantino et al., 2013a; Lau, Xie, & Zhao, 2008). An experimental design evaluates the statistical significance of the interactions of forecasting parameters, information sharing level and safety stock level to evaluate how they can contribute to improve or reduce performances. The analysis aims at giving some useful insights and managerial implications to determine guidelines of coordination in a competitive environment.

### 3. Supply chain simulation modeling

Following the leading research of Chen, Drezner, et al. (2000), Chatfield et al. (2004) and Dejonckheere et al. (2004), this study propose a discrete event simulation to identify the role of the ordering policy in controlling bullwhip effect, where the performances at each echelon derives mainly from the level of coordination among the partners of the supply chain.

The model represents a traditional four-echelon supply chain consisting of a customer, a retailer, a wholesaler, a distributor and a factory (see, Fig. 2) as for many previous studies in this field (Chatfield et al., 2004; Chatfield, 2013; Ciancimino et al., 2012; Costantino et al., 2013a, 2013b, 2014a). Fig. 2 depicts a visual representation of the supply chain in which, at any period, each echelon  $i$  receives orders from its downstream partner  $i - 1$ , satisfies these orders from his own stock and then issues an order to echelon  $i + 1$ . The retailer observes and satisfies the customer demand  $D_t$  and places orders with the wholesaler. All the

echelons employ a periodic review order-up-to (R, S) inventory policy in which the order-up-to level updates at the end of each review period ( $R$ ), with  $R = 1$ , according to the forecasting of the future demand.

The model presents the following assumptions (Ciancimino et al., 2012; Sterman, 1989; Wright & Yuan, 2008):

- The factory has an unlimited capacity to produce any quantity ordered by the distributor.
- The stocking capacity at any echelon is unlimited.
- The unfulfilled orders, due to out of stock, at any echelon are not lost but they become backlogs, to satisfy as soon as the inventory recovers.
- The transportation capacity between adjacent echelons is unlimited.
- The ordering and delivery lead-times are deterministic and fixed across the supply chain with ordering lead-time ( $Lo = R$ ) = 1 and delivery lead-time ( $Ld$ ) = 2.
- Orders are always positive or equal to zero, cancelations are not allowed (non-negativity condition).

The Eqs. (1)–(7) define the different state variables at each echelon  $i$  in each period  $t$ ; where  $i = 1, \dots, 4$ ; e.g.,  $i = 1$  stands for the retailer and  $i = 4$  stands for the factory, and we also refer to the customer as  $i = 0$  to adjust the model:

$$SL_t^i = SL_{t-1}^i + O_{t-1}^i - SR_{t-Ld}^{i+1} \quad (1)$$

$$SR_t^i = \text{Min}\{IO_t^i + B_{t-1}^i; I_{t-1}^i + SR_{t-Ld}^{i+1}\} \quad (2)$$

$$IO_t^i = O_{t-Lo}^{i-1} \quad (3)$$

$$I_t^i = I_{t-1}^i + SR_{t-Ld}^{i+1} - SR_t^i \quad (4)$$

$$B_t^i = B_{t-1}^i + IO_t^i - SR_t^i \quad (5)$$

$$NI_t^i = I_t^i - B_t^i \quad (6)$$

$$IP_t^i = I_t^i + SL_t^i - B_t^i \quad (7)$$

In each period  $t$ , each echelon  $i$  receives an amount of shipment  $SR_{t-Ld}^{i+1}$  issued by the upstream echelon  $i + 1$  at time  $t - Ld$ . Thus, the initial inventory level  $I_{t-1}^i$  increases by the shipment  $SR_{t-Ld}^{i+1}$  and at the same time decreases by the amount of  $SR_t^i$  released down to the echelon  $i - 1$  (see, Eq. (4)). The amount  $SR_t^i$  to ship to echelon  $i - 1$  is the lower value between the initial inventory  $I_{t-1}^i$  added to the incoming shipment  $SR_{t-Ld}^{i+1}$  and the order  $IO_t^i$  added to the backlog order  $B_{t-1}^i$  (see, Eq. (2)) where at the retailer (echelon  $i = 1$ ), the incoming order at time  $t$  is the observed customer demand at this time ( $IO_t^{i=1} = D_t$ ). Thus, the net inventory  $NI_t^i$  in Eq. (6) is equal to the difference between the available inventory level  $I_t^i$  and the backlog  $B_t^i$  at time  $t$ . The inventory position (7) is the accumulation of the amount in supply line  $SL_t^i$  in Eq. (1) and the net inventory level in Eq. (6). The order  $O_t^i$  of the echelon  $i$  to the echelon  $i + 1$  depends on the ordering policy.

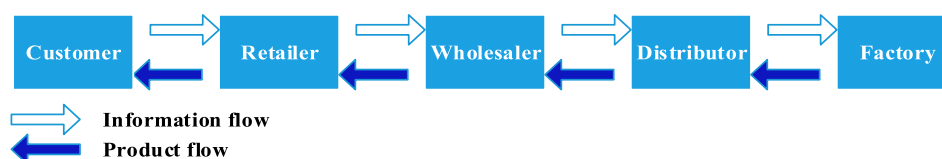


Fig. 2. A multi-echelon supply chain.

The Eqs. (8)–(15) represent the rules of the order-up-to policy:

$$O_t^i = \text{Max}\{(S_t^i - IP_t^i), 0\} \tag{8}$$

$$IP_t^i = S_{t-1}^i - IO_t^i \tag{9}$$

$$S_t^i = L\hat{D}_t^i + SS_t^i \tag{10}$$

$$SS_t^i = k\hat{\sigma}_t^i \tag{11}$$

$$\hat{S}_t^i = L\hat{D}_t^i + k\hat{\sigma}_t^i \tag{12}$$

$$\hat{D}_t^i = \frac{1}{n_i} \sum_{j=1}^{n_i} IO_{t-j+1}^i, \text{ for } \forall i > 1 \tag{13}$$

$$\hat{D}_t^R = \frac{1}{n_i} \sum_{j=1}^{n_i} D_{t-j+1}, \text{ for } i = 1 \tag{14}$$

(at the retailer)

In the periodic review order-up-to policy, at the end of each period  $t$ , each echelon issues a non-negative order  $O_t^i$  whenever the inventory position  $IP_t^i$  is lower than a specific target level  $S_t^i$  (order-up-to level) as in Eq. (8). The target inventory position for an echelon  $i$  at time  $t$ ,  $S_t^i$  relies on the expected demand over the total lead-time ( $L\hat{D}_t^i$ ) where  $L = R + Ld$  and  $\hat{D}_t^i$  is the one-period ahead demand forecast, as shown in Eq. (10), resulting in a dynamic target level that, every period  $t$ , follows the updated demand forecast. In order to account for demand variation, a safety stock component adds to the equation of the target inventory position, as in Eqs. (10)–(12). The amount of safety stock depends on the variation of incoming orders during the lead-time period ( $L$ ) and the service level ( $k$ ). Another common approach is to extend the lead-time to calculate the safety stock, instead of depending on the formula  $k\hat{\sigma}_t^i$  (Chatfield & Pritchard, 2013; Dejonckheere et al., 2004). In this model, we set  $k = 0$  and considered the safety stock term by extending the lead-time period by  $K_i$  so that the target inventory position  $S_t^i$  becomes as follow:

$$S_t^i = (L + K_i)\hat{D}_t^i \tag{15}$$

The demand forecast ( $\hat{D}_t^i$ ) is dynamically updated in each period  $t$  with the moving average forecasting technique which is commonly used in practice and research (Chen, Drezner, et al., 2000; Disney & Lambrecht, 2008). The only parameter required for the moving average forecasting is the number of past periods  $n_i$  used to average the demand. Specifically, at the end of each period  $t$ , all echelons other than the retailer (echelon  $i > 1$ ) estimate the expected demand in the next period (one-period ahead demand forecast,  $\hat{D}_t^i$ ) based on the average of the incoming orders from the adjacent downstream echelon over the most recent  $n_i$  periods ( $IO_{t-n_i+1}^i, \dots, IO_t^i$ ) (see, Eq. (13)). Eq. (13) is a general equation that can be used to obtain the demand forecast at any echelon where  $IO_{t-j+1}^i$  represents the incoming order from the downstream echelon  $i - 1$  to echelon  $i$  at time  $t - j + 1$  where  $j = 1, \dots, n_i$ . At the retailer (echelon  $i = 1$ ), the demand forecast is adjusted in the same manner but based on the actual customer demand data ( $D_{t-n_i+1}, \dots, D_t$ ) as shown in Eq. (14) which is a special case of (13). The mean demand over the lead time is estimated by multiplying the next period's demand forecast by the lead time added to the safety stock parameter which determines the target inventory position in Eq. (15).

The last Eq. (15) shows that each echelon  $i$  in the supply chain can use his own forecasting method and his own parameter of the ordering policy.

### 3.1. Performance measures

The study analyzes and quantifies supply chain under three different performances: bullwhip effect ratio, inventory variance ratio and average service level.

#### 3.1.1. Bullwhip effect ratio

The bullwhip effect ratio expresses the amplification of demand variability across the supply chain. In particular, Chen, Drezner, et al. (2000) quantified bullwhip effect ( $BWE_i$ ) analytically in terms of the variance of the orders ( $\sigma_{O_i}^2$ ) at echelon  $i$  relative to the variance of the demand at the retailer:

$$BWE_i = \frac{\sigma_{O_i}^2 / \mu_{O_i}}{\sigma_D^2 / \mu_D} \tag{16}$$

where  $\mu_{O_i}$  represents the average of the orders at echelon  $i$ ,  $\mu_D$  is the average of the customer demand and  $\sigma_D^2$  is the variance of the customer demand. It is expected that  $\mu_{O_i} = \mu_D$  in the long term run and, therefore, the measure turns into  $BWE_i = \sigma_{O_i}^2 / \sigma_D^2$ . Dejonckheere et al. (2004) used the same metric as a measure of bullwhip effect and called it the 'Variance Ratio'. They stated that *Variance Ratio*  $> 1$  results in a bullwhip; *Variance Ratio*  $< 1$  results in order smoothing; *Variance Ratio* = 1 results in a "pass-on-orders" policy, where the ordering pattern exactly follows the demand pattern.

#### 3.1.2. Inventory variance ratio

The second measure is the inventory variance ratio. Disney and Towill (2003a) were the first to propose this measure to evaluate the degree of inventory stability, as it quantifies the fluctuations in net inventory variability ( $\sigma_{NI_i}^2$ ) relative to the fluctuation in demand variability ( $\sigma_D^2$ ):

$$InvR_i = \frac{\sigma_{NI_i}^2}{\sigma_D^2} \tag{17}$$

It can also measure the amplification in inventory instability as we move up the supply chain, similar to the bullwhip effect ratio. An increase in inventory variance would result in higher holding and backlog costs, lower service level and increasing average inventory costs per period.

#### 3.1.3. Average service level

The average service level quantifies the percentage of items delivered immediately by the echelon  $i$  to satisfy an incoming order (Zipkin, 2000). Service level or fill rate ( $SL_t^i$ ) computes every review time  $R$  over the effective delivery time (i.e.,  $IO_t^i > 0$ ) as in Eq. (18). Its time series constitutes the history of the effectiveness of the delivery system, where  $SR_t^i$  stands for the shipment from echelon  $i$  to echelon  $i - 1$ ,  $B_{t-1}^i$  stands for the initial backlog at echelon  $i$ , and  $IO_t^i$  is the incoming order to echelon  $i$ . The effective simulation time is equivalent to the summation of all periods with  $IO_t^i > 0$ ; hence,  $T_{eff} \leq T$ .

$$SL_t^i = \begin{cases} \frac{SR_t^i - B_{t-1}^i}{IO_t^i} \times 100 & \text{if } SR_t^i - B_{t-1}^i > 0 \\ 0 & \text{if } SR_t^i - B_{t-1}^i \leq 0 \end{cases} \tag{18}$$

$$ASL_i = \frac{\sum_{t=1}^{T_{eff}} SL_t^i}{T_{eff}} \tag{19}$$

The average service level ( $ASL_i$ ) is computed only over the effective simulation time ( $T_{eff}$ ) as in Eq. (19).

### 3.2. Verification and validation of the simulation model

The simulation model, developed in SIMUL8, followed a verification and validation process with the analytical work of Chen, Drezner, et al. (2000), the control engineering work of Dejonckheere et al. (2004) and the simulation work of Chatfield et al. (2004). Chen, Drezner, et al. (2000) developed a closed-form expression for quantifying the bullwhip effect ratio in a two-stage supply chain, generalizing to multi-echelon systems through



**Table 1**  
Simulation model validation results.

Comparison of TSC results			$L + K_i = 5\forall i$	$n_i = 19\forall i$	$D \sim N(100, 10^2)$		
Echelon $i$	TSC (a)	Chen et al. (2000) (b)	Dejonckheere et al. (2004) (c)	Chatfield et al. (2004) (d)	% (a–b)	% (a–c)	% (a–d)
Retailer	<b>1.67</b>	1.66	1.67	1.67	0%	0.13%	0.12%
Wholesaler	<b>3.00</b>	2.77	2.99	2.99	8%	0.27%	0.32%
Distributor	<b>5.74</b>	4.61	5.72	5.72	20%	0.36%	0.36%
Factory	<b>11.45</b>	7.68	11.43	11.43	33%	0.16%	0.13%
Average percentage error (%)					<b>15%</b>	<b>0.23%</b>	<b>0.23%</b>

**Table 2**  
Information sharing scenarios (incoming order to each echelon).

Scenario #	Retailer	Wholesaler	Distributor	Factory
1	CD	RO	WO	DO
2	CD	CD	WO	DO
3	CD	CD	CD	DO
4	CD	CD	CD	CD
5	CD	RO	RO	RO
6	CD	RO	WO	WO

CD = customer demand, RO = retailer order, WO = wholesaler order, DO = distributor order

multiple applications (i.e. a product of several individual stage amplification values) as shown in the following equation:

$$\frac{\sigma_{o_i}^2}{\sigma_b^2} \geq \prod_{i=1}^m \left( 1 + \frac{2L_i}{n_i} + \frac{2L_i^2}{n_i^2} \right) \forall i \quad (20)$$

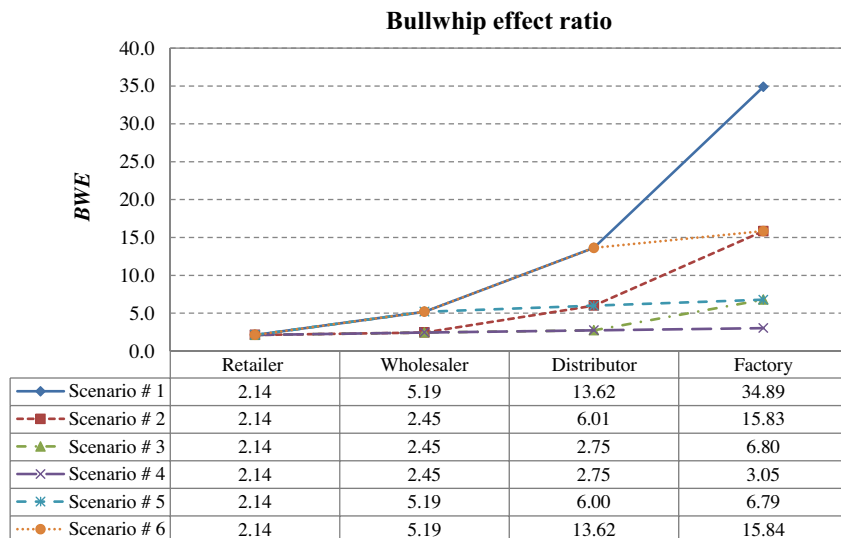
Dejonckheere et al. (2004) considered a control theoretic approach to quantify the bullwhip effect and validated their model with Chen, Drezner, et al. (2000), whereas Chatfield et al. (2004) adopted a simulation approach to quantify the bullwhip effect and validated their results with both Dejonckheere et al. (2004) and Chen, Drezner, et al. (2000). We compare the results of our model with them all, setting the same simulation and operational parameters in a validation test of 20 replications for a length of 5200 periods, each with a warm-up period of 200 periods (Chatfield et al., 2004; Dejonckheere et al., 2004). For the other simulation experiments in the paper, since the simulation model is a non-terminating system, the number of replications are selected based on a 95% confidence level

and absolute precision level (half width/mean) lower than 5% on the bullwhip effect measures (Chatfield et al., 2004; Chatfield et al., 2013; Robinson, 2005).

The demand pattern follows a normal distribution with an average of 100 and a standard deviation of 10 (i.e.,  $N(100, 10^2)$ ). The moving average parameter was set to  $n_i = 19, \forall i$ , and the safety stock component was set to  $K_i = 2$ , i.e., the value of  $L + K_i = 5$  where  $L = R + Ld$  and  $R = 1$  (Chatfield et al., 2004; Dejonckheere et al., 2004). We applied these values in Eq. (20) to get the bullwhip effect ratio at each echelon  $i$  based on Chen, Drezner, et al. (2000), where  $i = 1, \dots, m$  and  $m = 4$ , and  $L_i = L + K_i$  to consider the safety stock component. Table 1 shows that the simulation model works as expected. The closed form expression of Chen, Drezner, et al. (2000) does not consider the interactions in the model (Chatfield, 2013, 2004), therefore, there is a considerable difference between the average percentage error between (a, c, d) and (b). The average percentage error of 0.23% with the other two simulation models is mainly due to the different random seeds in the different models and to the non-negativity of orders (allowed in the original ones).

**4. The value of information sharing**

In literature, a general assumption of information sharing is that all the partners in the supply chain would have access in real time to same information (Dejonckheere et al., 2004). Considering the periodic review order-up-to level strategy, the only set of sensible information is the value of the demand: having information on inventory or capacity of the downstream and upstream echelons wouldn't change the value of the orders issued by any partner. In this study, we are seeking to quantify the impact of different configurations of partial demand sharing on supply chain performances as for cases when downstream echelons might



**Fig. 3.** Bullwhip effect ratio in different information sharing scenarios.

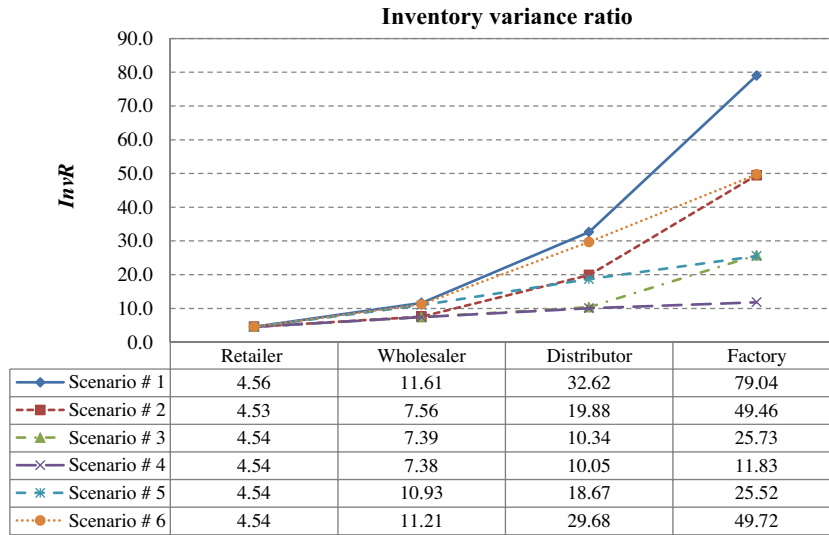


Fig. 4. Inventory variance ratio in different information sharing scenarios.

collaborate without coordinating with the upstream ones (Son & Sheu, 2008). Table 2 illustrates a sample of significant information sharing scenarios to represent a gradually increasing level of collaboration, where not all the partners have complete visibility on the demand or orders:

1. Scenario #1 or Traditional Supply Chain (TSC): the benchmark case described above, in which the retailer is the only partner that has access to the customer demand while the other partners receive the downstream echelon's orders.
2. Scenario #2 or Downstream Collaboration (DC) both the retailer and the wholesaler have access to the customer demand.
3. Scenario #3 all the partners in the supply chain, except the factory, have access to the customer demand.
4. Scenario #4 or Information-Enriched Supply Chain (IESC) highest level of information sharing in which all the partners have access to the customer demand.
5. Scenario #5 limited collaboration among the upstream echelons where both the distributor and the factory have access to the incoming orders from the retailer to the wholesaler, without knowing the customer demand.

6. Scenario #6 or Upstream Collaboration (UC) very limited collaboration between the distributor and the factory in which the factory has access to the incoming orders at the distributor.

The level of information sharing changes the input data of the forecast at any echelon. In the scenarios #2, #3 and #4, all the partners that have access to the demand use Eq. (14) instead of Eq. (13), meaning that the target level is no more affected by the variations of the orders coming from the downstream echelons but it relies directly on the customer demand. In the scenarios #5 and #6, all the partners that have access to the downstream echelons orders use these values in their forecasts, instead of their incoming order time series, to represent the customer demand with a lower distortion.

The simulation settings for the experiment are considered as follows:

- customer demand follows the normal distribution with  $\mu_D = 30$  and  $\sigma_D^2 = 3^2$  where  $\sigma_D$  is selected significantly smaller than  $\mu_D$ , so that the occurrence of negative demand observations is negligible;

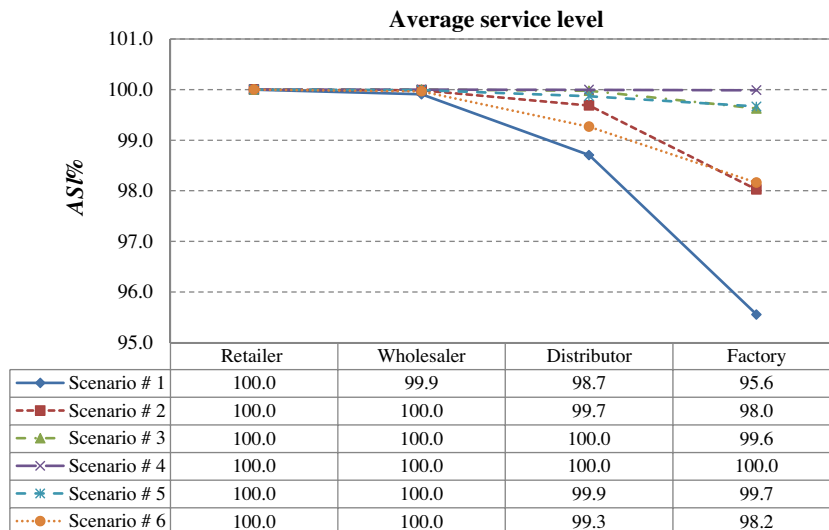


Fig. 5. Average service level in different information sharing scenarios.

- all echelons in the supply chain use the same ordering policy with  $K_i = 1, \forall i$ , and the same forecasting method with  $n_i = 10, \forall i$  where these settings are the average and common values employed for these parameters in the related literature (Chatfield et al., 2004; Dejonckheere et al., 2003; Dejonckheere et al., 2004; Wright & Yuan, 2008). In particular, when  $n_i = 10, \forall i$ , the forecast variance is  $\sigma_D^2 = \sigma_D^2/n_i = 0.9$  that means a percentage error of 3% on the average value.
- for each scenario, the simulation model runs for 20 replications of 1200 periods, each with a warm-up of 200 periods (95% confidence level with absolute precision level lower than 5%).

Fig. 3 confirms that the bullwhip effect act in all the scenarios (i.e.,  $BWE_i > 1$ ) regardless information are shared or not. However, Scenario #1 shows the highest bullwhip effect at all echelons with a ratio geometrically increasing as moving from the retailer to the factory and a variability about 35 times the customer demand. Scenario #4 represents the lower bound of the bullwhip effect as the distortion of the demand is null and the effect derives only from the value of lead times and the structure of the inventory control policy. Increasing the information sharing level among the

downstream echelons shows a considerable effect throughout the supply chain and especially at the most upstream echelons, as in Scenarios #2–6. For instance, the collaboration between the retailer and the wholesaler in Scenario #2 (downstream collaboration) allows a decrease of more than 50% of the bullwhip effect, i.e. from 5.19 to 2.45 at the wholesaler, from 13.62 to 6.01 at the distributor and from 34.89 to 15.83 at the factory. More collaboration leads to a reduction in the propagation rate: bullwhip effect ratio increases geometrically over the echelons that do not participate in collaboration (e.g., Scenarios #1, #2, #6) and increase linearly over the echelons that participate (e.g., Scenarios #3, #4, #5). Furthermore, the results indicate that downstream collaboration is more effective than upstream collaboration as, once the amplification starts, it is more difficult to counteract.

In Fig. 4, the behavior in terms of inventory variance ratio resembles to a considerable degree the bullwhip effect in Fig. 3. The lack of collaboration leads to a large increase in the inventory instability moving upstream in the supply chain as a negative consequence of the bullwhip effect. The collaboration through information sharing have both local and global effect: comparing the Upstream Collaboration (Scenario #6) with the Traditional Supply

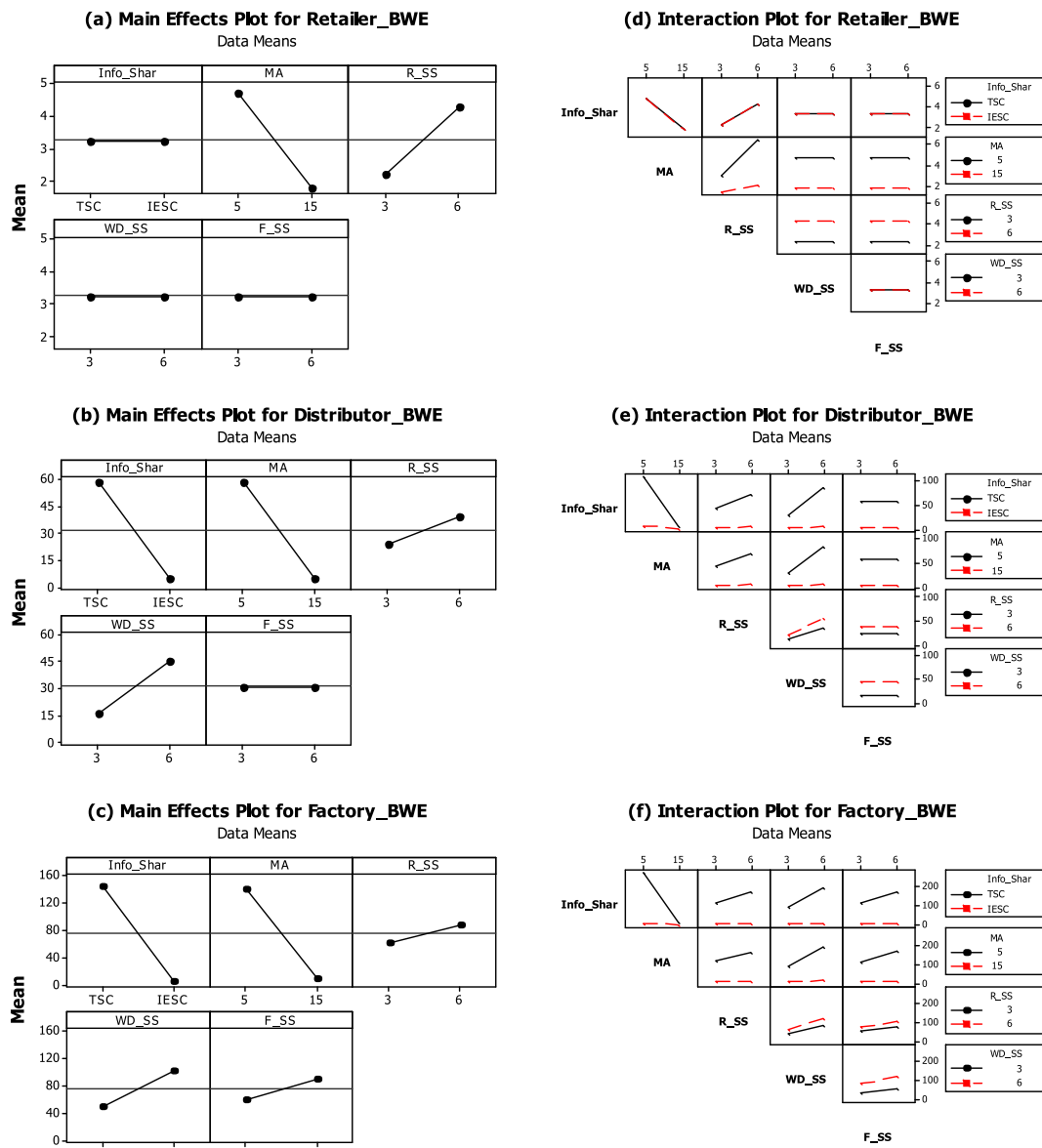


Fig. 6. The sensitivity of the bullwhip effect to the experimental factors.

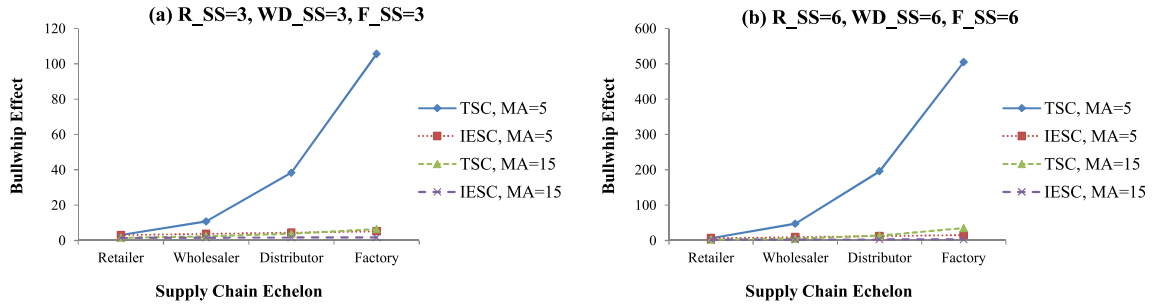


Fig. 7. Interaction effect between MA and Info\_Shar on bullwhip effect.

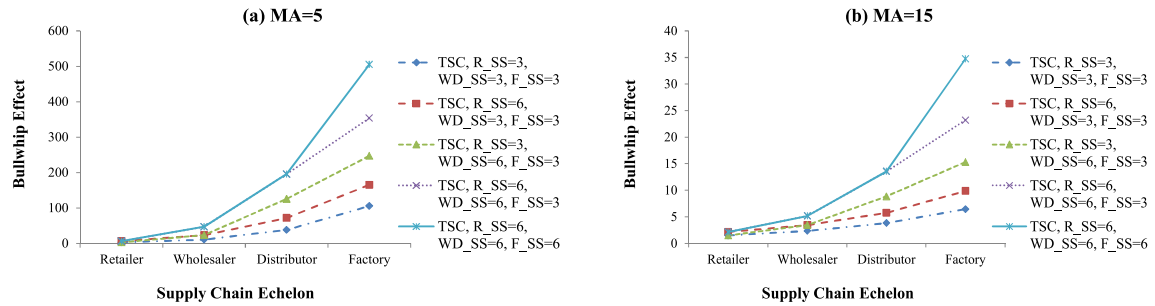


Fig. 8. Interaction effect of the safety stock levels on the bullwhip effect.

Table 3  
ANOVA results for the bullwhip effect at the different echelons.

Source of Bullwhip Effect Variation	Retailer BWE			Wholesaler BWE			Distributor BWE			Factory BWE		
	DF	F	P	DF	F	P	DF	F	P	DF	F	P
Main Effects	5	67128.5	0.00	5	17569.7	0.00	5	20315.5	0.00	5	19616.6	0.00
Info_Shar	1	0.0	1.00	1	27398.3	0.00	1	42369.5	0.00	1	46110.87	0.00
MA	1	224350.8	0.00	1	44520.7	0.00	1	42849.8	0.00	1	41438.69	0.00
R_SS	1	111291.6	0.00	1	8498.9	0.00	1	3349.1	0.00	1	1768.72	0.00
WD_SS	1	0.0	1.00	1	7430.8	0.00	1	13009.2	0.00	1	6732.51	0.00
F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	2032.21	0.00
2-Way Interactions	10	5250.9	0.00	10	3976.2	0.00	10	6007.2	0.00	10	5443.32	0.00
Info_Shar*MA	1	0.0	1.00	1	19830.7	0.00	1	33586.9	0.00	1	36714.74	0.00
Info_Shar*R_SS	1	0.0	1.00	1	3675.5	0.00	1	2500.0	0.00	1	1515.47	0.00
Info_Shar*WD_SS	1	0.0	1.00	1	4538.7	0.00	1	10968.0	0.00	1	6142.67	0.00
Info_Shar*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	1867.5	0.00
MA*R_SS	1	52509.0	0.00	1	5816.8	0.00	1	2515.2	0.00	1	1304.12	0.00
MA*WD_SS	1	0.0	1.00	1	5379.6	0.00	1	10133.0	0.00	1	5037.56	0.00
MA*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	1550.48	0.00
R_SS*WD_SS	1	0.0	1.00	1	520.6	0.00	1	368.9	0.00	1	128.68	0.00
R_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	35.39	0.00
WD_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	136.57	0.00
3-Way Interactions	10	0.0	1.00	10	732.5	0.00	10	1132.3	0.00	10	772.11	0.00
Info_Shar*MA*R_SS	1	0.0	1.00	1	2983.8	0.00	1	2003.3	0.00	1	1153.9	0.00
Info_Shar*MA*WD_SS	1	0.0	1.00	1	3380.3	0.00	1	8672.7	0.00	1	4625.08	0.00
Info_Shar*MA*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	1433.93	0.00
Info_Shar*R_SS*WD_SS	1	0.0	1.00	1	537.1	0.00	1	373.1	0.00	1	129.69	0.00
Info_Shar*R_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	35.46	0.00
Info_Shar*WD_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	137.63	0.00
MA*R_SS*WD_SS	1	0.0	1.00	1	423.5	0.00	1	274.1	0.00	1	86.82	0.00
MA*R_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	24.12	0.00
MA*WD_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	92.4	0.00
R_SS*WD_SS*F_SS	1	0.0	1.00	1	0.0	1.00	1	0.0	1.00	1	2.07	0.15
Residual Error	614			614			614			614		
Total	639			639			639			639		

Chain (Scenario #1), the inventory variance ratio decreases from 32.62 to 29.68 at the distributor (local effect), from 79.04 to 49.72 at the factory (global effect) and slightly from 11.61 to 11.21 at the wholesaler (global effect).

The behavior of the average service level is a reverse pattern of the bullwhip effect and inventory variance, as for Fig. 5. It is clear that the average service level ( $ASL_i$ ) decreases as we move upstream in the supply chain especially when the collaboration level is low



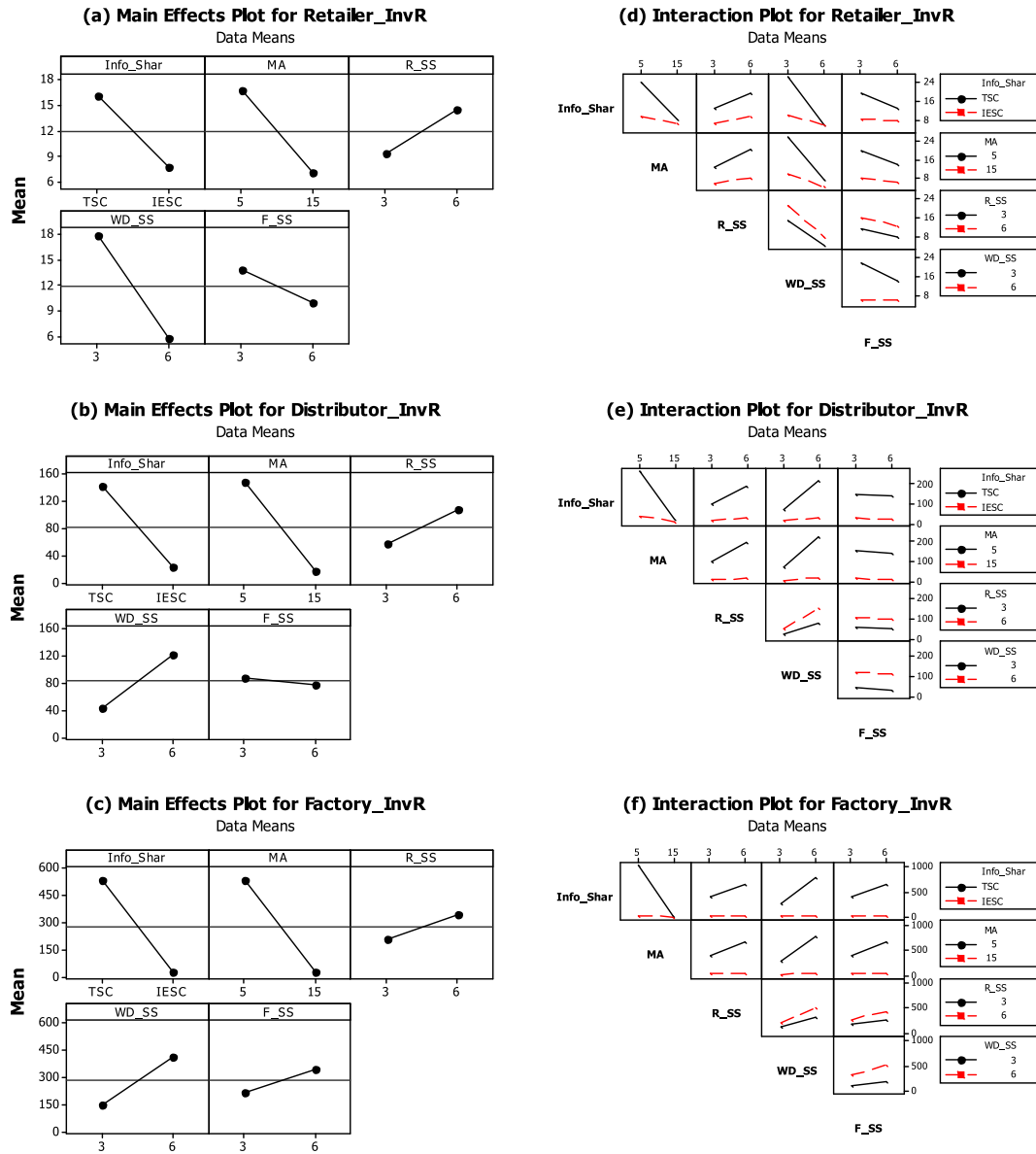


Fig. 9. The sensitivity of the inventory variance to the experimental factors.

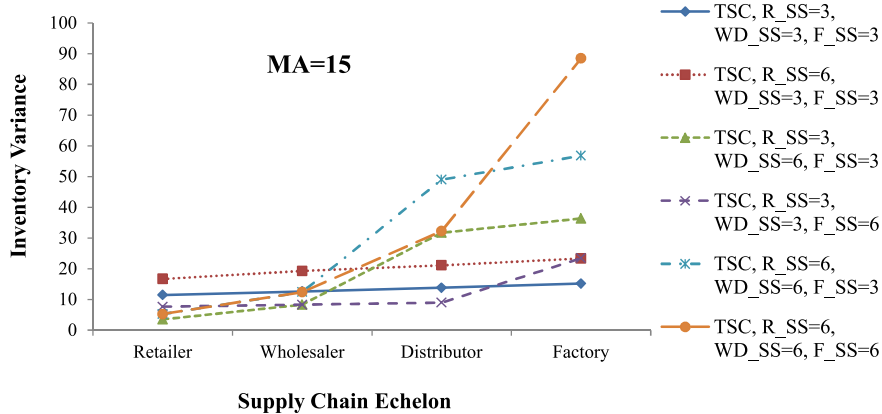


Fig. 10. Impact of different settings of safety stock level on the inventory variance.

or absent. This conclusion confirms the recent study of Chatfield et al. (2013) where they investigated the existence and magnitude of stock out propagation and amplification in inventory systems.

This means that the upstream echelons are not able to handle properly the variability of the incoming orders although the downstream are successful to do that. The distributor and the factory

that suffer the problem would have to increase the level of their safety stock to handle this situation. Interestingly, as the level of collaboration increases, the average service level improves at the higher upstream echelons.

The best scenario that achieves the lowest bullwhip effect and inventory variance ratio and the highest average service level is the Information-Enriched Supply Chain in which all echelons have access to the customer demand. The results show that, when possible, local partnerships (downstream or upstream) are anyway recommended, as they can lead to decrease the variance amplification at any echelon whilst achieving improvements on inventory performance.

**5. Experimental design**

Forecasting and inventory control parameters are key causes of the bullwhip effect and inventory instability that could influence the impact of information sharing. To extend the results of the analysis, we design a factorial experiment with five factors on two levels each, according to the hypothesis of Chatfield et al. (2004) and Barlas and Gunduz (2011):

- 1- Information sharing (Info\_Shar): TSC and IESC
- 2- Moving average parameter (MA): 5 and 15
- 3- Safety stock level at the most downstream echelon (i.e., retailer): 3 and 6
- 4- Safety stock level at the middle echelons (i.e., wholesaler and distributor): 3 and 6
- 5- Safety stock level at the most upstream echelon (i.e., factory): 3 and 6

To conduct this experiment, we run all the possible combinations of the five factors and levels, having 32 possible

combinations. Each simulation consists of 20 replications of 1200 periods each, with the first 200 periods of warm-up. In this case, we assumed the customer demand follows a normal distribution with  $\mu_D = 30$  and  $\sigma_D = 3$ . The value of  $\sigma_D$  is selected significantly smaller than  $\mu_D$  in order to avoid the occurrence of negative demand observations since it is also assumed that cancellations are not allowed which means that orders of each echelon in the supply chain are always positive or equal to zero (Hussain et al., 2012).

The two levels of information sharing factor are the Traditional Supply Chain (TSC) and the Information Enriched Supply Chain (IESC) to represent the extreme conditions of performances where the bullwhip effect increases, respectively, geometrically and linearly at all echelons. The difference between TSC and IESC indicating how the input data for the demand forecast is different in each case is discussed in the previous section.

The experimental factor MA represents the moving average parameter  $n_i$  (i.e.,  $n_i = MA, \forall i$ ) in Eqs. (13) and (14), which is the only parameter to regulate the accuracy of the forecasting technique, being considered as one of the major causes of the bullwhip effect in either TSC or IESC (Chen, Drezner, et al., 2000; Dejonckheere et al., 2003, 2004). In this case, where the demand pattern is normal, an increase in MA results uniquely in a more accurate forecast as, according to the central limit theorem, the estimation error decreases with the increase of the size of the sample. With this simple assumption, two levels are sufficient to describe the relative impact that an increase of the forecast accuracy has on the supply chain performances whilst providing further insights on the interaction between MA and other experimental factors. Therefore, the values of the two levels of MA are selected to have a high likelihood of considerable main effect and interaction with the other parameters, whilst covering the MA range reported in the previous literature (Chandra &

**Table 4**  
ANOVA results for the inventory variance at the different echelons.

Source of Inventory Variance Variation	Retailer InvR			Wholesaler InvR			Distributor InvR			Factory InvR		
	DF	F	P	DF	F	P	DF	F	P	DF	F	P
Main Effects	5	3292.3	0.00	5	6303.1	0.00	5	4468.6	0.00	5	3853.01	0.00
Info_Shar	1	3241.2	0.00	1	8470.6	0.00	1	7890.2	0.00	1	7979.09	0.00
MA	1	4412.2	0.00	1	18528.8	0.00	1	9598.6	0.00	1	7953.39	0.00
R_SS	1	1227.2	0.00	1	4177.1	0.00	1	1238.5	0.00	1	570.37	0.00
WD_SS	1	6914.5	0.00	1	68.1	0.00	1	3464.1	0.00	1	2226.13	0.00
F_SS	1	666.5	0.00	1	270.8	0.00	1	51.5	0.00	1	536.05	0.00
2-Way Interactions	10	910.2	0.00	10	932.1	0.00	10	1336.4	0.00	10	1305.88	0.00
Info_Shar*MA	1	2003.5	0.00	1	5636.4	0.00	1	6154.6	0.00	1	6982.11	0.00
Info_Shar*R_SS	1	134.5	0.00	1	863.8	0.00	1	883.6	0.00	1	507.23	0.00
Info_Shar*WD_SS	1	3241.1	0.00	1	1.5	0.22	1	2478.5	0.00	1	1939.28	0.00
Info_Shar*F_SS	1	386.4	0.00	1	131.5	0.00	1	2.2	0.14	1	541.34	0.00
MA*R_SS	1	325.7	0.00	1	2294.1	0.00	1	1011.0	0.00	1	487.67	0.00
MA*WD_SS	1	2010.5	0.00	1	7.6	0.01	1	2532.7	0.00	1	1913.58	0.00
MA*F_SS	1	219.4	0.00	1	53.1	0.00	1	4.1	0.04	1	463.68	0.00
R_SS*WD_SS	1	114.7	0.00	1	14.7	0.00	1	295.6	0.00	1	75.11	0.00
R_SS*F_SS	1	0.0	1.00	1	0.0	0.87	1	0.3	0.57	1	30.64	0.00
WD_SS*F_SS	1	666.5	0.00	1	317.7	0.00	1	1.6	0.20	1	118.19	0.00
3-Way Interactions	10	304.1	0.00	10	100.9	0.00	10	320.5	0.00	10	304.41	0.00
Info_Shar*MA*R_SS	1	61.2	0.00	1	597.3	0.00	1	727.4	0.00	1	445.64	0.00
Info_Shar*MA*WD_SS	1	2003.4	0.00	1	0.3	0.57	1	1942.9	0.00	1	1707.98	0.00
Info_Shar*MA*F_SS	1	204.7	0.00	1	61.4	0.00	1	0.6	0.42	1	469.88	0.00
Info_Shar*R_SS*WD_SS	1	134.5	0.00	1	62.7	0.00	1	274.1	0.00	1	71.55	0.00
Info_Shar*R_SS*F_SS	1	0.0	0.93	1	0.5	0.48	1	0.3	0.62	1	31.83	0.00
Info_Shar*WD_SS*F_SS	1	386.4	0.00	1	163.6	0.00	1	7.9	0.01	1	118.14	0.00
MA*R_SS*WD_SS	1	29.0	0.00	1	43.2	0.00	1	242.4	0.00	1	63.34	0.00
MA*R_SS*F_SS	1	2.8	0.10	1	4.3	0.04	1	0.2	0.67	1	26.99	0.00
MA*WD_SS*F_SS	1	219.4	0.00	1	74.9	0.00	1	9.0	0.00	1	103.98	0.00
R_SS*WD_SS*F_SS	1	0.0	1.00	1	0.3	0.61	1	0.0	0.95	1	4.79	0.03
Residual Error	614			614			614			614		
Total	639			639			639			639		

Grabis, 2005; Chatfield et al., 2004; Dejonckheere et al., 2003, 2004; Son & Sheu, 2008; Wright & Yuan, 2008). In particular, when MA is set to the low level ( $n_i = MA = 5, \forall i$ ) then the forecast variance is  $\sigma_D^2 = \sigma_D^2/n_i = 1.8$  that means a percentage error of about 4.5% on the average value; when MA is set to the high level ( $n_i = MA = 15, \forall i$ ),  $\sigma_D^2 = 0.6$  and the percentage error decreases to

2.5%. If the patterns were not normal, the experimental design should first support in finding the best value of MA, investigating different levels of the parameter according to the weight of trend, seasonality and autocorrelation of the demand.

In the order-up-to policy, the safety stock parameter ( $K_i$ ) is the only one to control. The work of Barlas and Gunduz (2011) showed

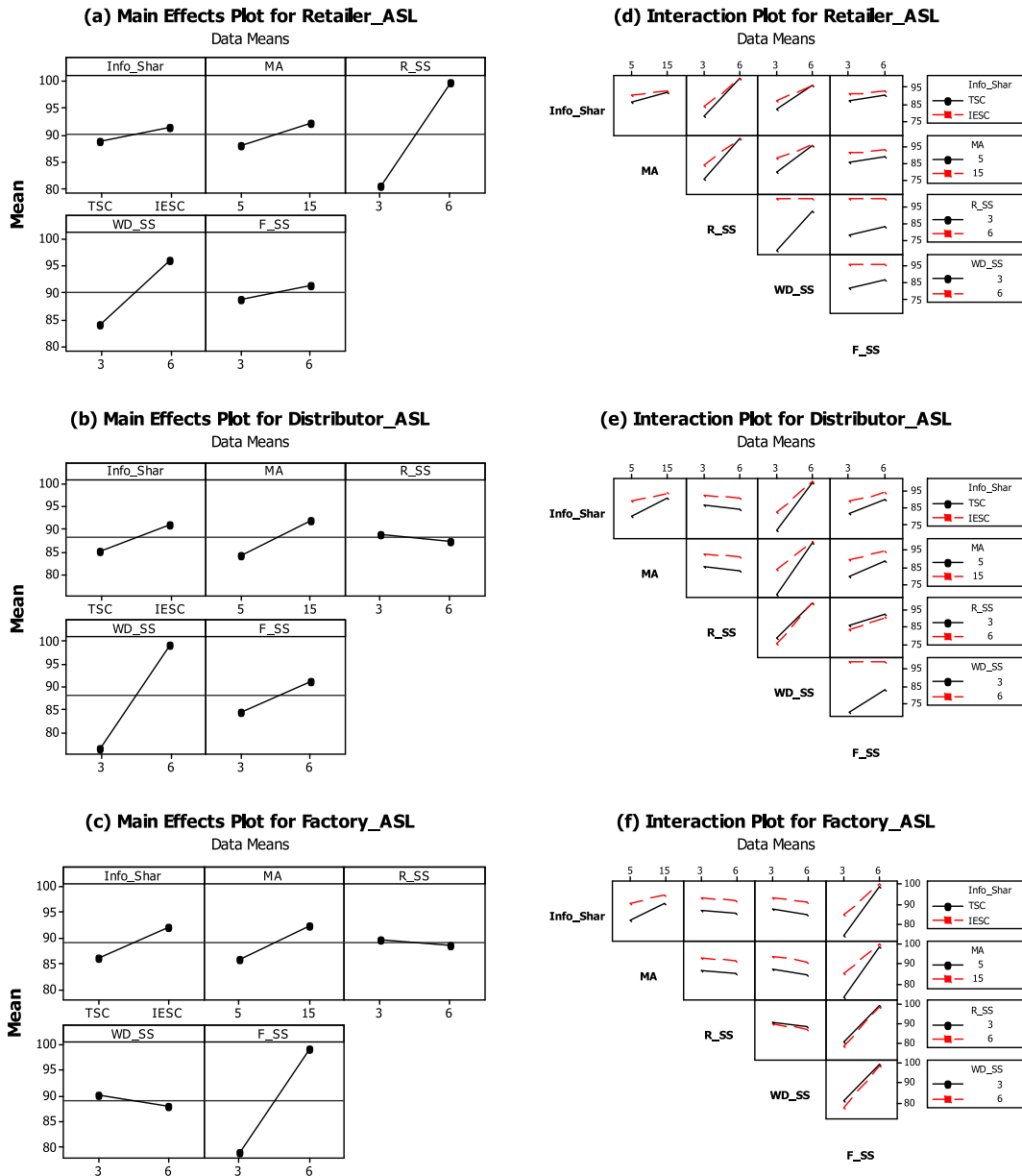


Fig. 11. The sensitivity of the average service level to the experimental factors.

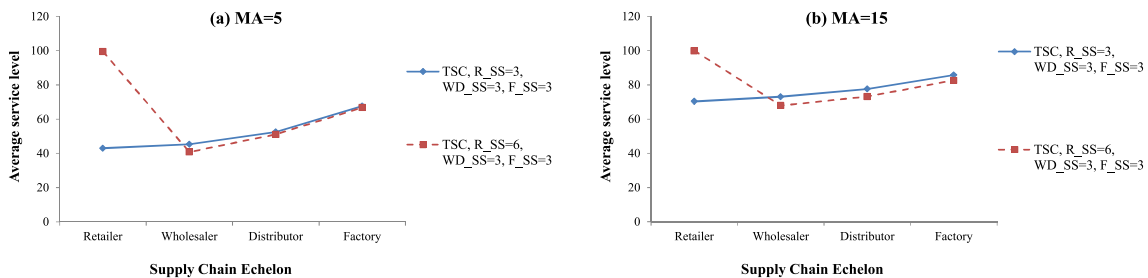


Fig. 12. The impact of safety stock level changing on average service level.

**Table 5**  
ANOVA results for the average service level at the different echelons.

Source of Service Level Variation	Retailer ASL			Wholesaler ASL			Distributor ASL			Factory ASL		
	DF	F	P	DF	F	P	DF	F	P	DF	F	P
Main Effects	5	11871.9	0.00	5	54697.9	0.00	5	39846.5	0.00	5	13470.29	0.00
Info_Shar	1	862.3	0.00	1	8192.2	0.00	1	10356.9	0.00	1	5210.95	0.00
MA	1	1986.9	0.00	1	20027.2	0.00	1	18422.6	0.00	1	5902.13	0.00
R_SS	1	40947.1	0.00	1	1743.9	0.00	1	1012.8	0.00	1	206.22	0.00
WD_SS	1	14904.9	0.00	1	236448.2	0.00	1	155675.4	0.00	1	804.55	0.00
F_SS	1	658.2	0.00	1	7077.9	0.00	1	13764.7	0.00	1	55227.63	0.00
2-Way Interactions	10	2155.0	0.00	10	4044.5	0.00	10	3903.9	0.00	10	733.57	0.00
Info_Shar*MA	1	343.7	0.00	1	2422.1	0.00	1	3210.3	0.00	1	489.53	0.00
Info_Shar*R_SS	1	821.1	0.00	1	0.2	0.63	1	4.6	0.03	1	3.31	0.07
Info_Shar*WD_SS	1	862.3	0.00	1	8190.5	0.00	1	7291.3	0.00	1	8.49	0.00
Info_Shar*F_SS	1	69.2	0.00	1	449.2	0.00	1	682.7	0.00	1	2908.72	0.00
MA*R_SS	1	1924.2	0.00	1	157.0	0.00	1	71.7	0.00	1	0.19	0.66
MA*WD_SS	1	1444.4	0.00	1	20024.7	0.00	1	14218.6	0.00	1	0.97	0.33
MA*F_SS	1	68.3	0.00	1	380.9	0.00	1	937.9	0.00	1	3433.59	0.00
R_SS*WD_SS	1	14732.3	0.00	1	1743.1	0.00	1	685.5	0.00	1	0.04	0.84
R_SS*F_SS	1	625.9	0.00	1	0.2	0.63	1	4.9	0.03	1	104.86	0.00
WD_SS*F_SS	1	658.2	0.00	1	7076.9	0.00	1	11931.1	0.00	1	386.05	0.00
3-Way Interactions	10	377.2	0.00	10	351.4	0.00	10	258.8	0.00	10	27.91	0.00
Info_Shar*MA*R_SS	1	317.9	0.00	1	27.7	0.00	1	19.0	0.00	1	21	0.00
Info_Shar*MA*WD_SS	1	343.7	0.00	1	2421.2	0.00	1	1624.2	0.00	1	126.76	0.00
Info_Shar*MA*F_SS	1	17.3	0.00	1	40.7	0.00	1	44.3	0.00	1	15.19	0.00
Info_Shar*R_SS*WD_SS	1	821.1	0.00	1	0.2	0.63	1	11.5	0.00	1	2.09	0.15
Info_Shar*R_SS*F_SS	1	59.0	0.00	1	12.5	0.00	1	18.1	0.00	1	5.3	0.02
Info_Shar*WD_SS*F_SS	1	69.2	0.00	1	449.0	0.00	1	330.0	0.00	1	33.67	0.00
MA*R_SS*WD_SS	1	1391.0	0.00	1	156.8	0.00	1	8.1	0.01	1	1.58	0.21
MA*R_SS*F_SS	1	58.2	0.00	1	25.2	0.00	1	23.1	0.00	1	13.38	0.00
MA*WD_SS*F_SS	1	68.3	0.00	1	380.7	0.00	1	508.7	0.00	1	59.39	0.00
R_SS*WD_SS*F_SS	1	625.9	0.00	1	0.3	0.62	1	1.3	0.25	1	0.7	0.40
Residual Error	614			614			614			614		
Total	639			639			639			639		

that increasing the safety stock level increases the bullwhip effect even assuming the same  $K_i$  value at all the echelons. To deeply investigate the interaction among the different safety stock levels across the supply chain and identify the best allocation of inventory, we define three different factors dividing the supply chain into three zones, where the values of R\_SS, WD\_SS and F\_SS represent the ordering level  $L + K_i$ . For instance, R\_SS = 3 means that there is no safety stock or  $K_i = 0$  where  $L = 3$  is the same at all echelons. As for the other two parameters of the experimental design, when the demand pattern is normal, the effect of increasing the safety stock reflects in the same way on the supply chain performances so two levels are sufficient to entirely describe the interactions with the others.

5.1. Analysis of bullwhip effect sensitivity

Fig. 6 presents the sensitivity of the bullwhip effect of each echelon  $i$  to the different factors. The figure consists of the main effects of the factors (see, Fig. 6a–c) and of the interaction effects between the different factors (see, Fig. 6d–f). Since the conclusions for the bullwhip effect at the wholesaler are the same as at the distributor, we exclude the wholesaler’s plot and present only the response for the retailer, distributor and factory.

The strongest main effect on the bullwhip effect ratio is due to the MA value where increasing the averaging time reduces the bullwhip effect at all echelons. The second important factor is the information sharing level with no impact on the retailer as it always receives and collects the customer demand. The safety stock level has the third important main effect where increasing the safety stock level at any of the echelons leads to increase the bullwhip effect at the current echelon (local effect) and at the upstream echelons (global effect) as well. Therefore, the safety stock policy at the downstream echelons contributes to the level of instability at the upstream echelons. This result is a good

motivation for supply chain managers to seek for partnerships with other partners in order to restrict the propagation of information distortion. The strong interaction between MA and Info\_Shar at all echelons is evident in Fig. 7, in particular when information are not shared, where selecting the appropriate forecasting is a crucial task to suppress the bullwhip effect.

The other significant interactions relate to the safety stock levels, confirming their role in disturbing the transmission of the information. The two plots in Fig. 8 exhibit some examples of those interactions at two different levels of MA.

Table 3 illustrates the analysis of variance (ANOVA) to show if each term is statistically significant. At the retailer, where demand is known, there is only a statistical significant effect between MA and R\_SS. At the upstream echelons there are 2-way and 3-way interaction effects of statistical significance that confirm the findings from the interaction plots.

5.2. Analysis of inventory variance ratio sensitivity

As for bullwhip effect ratio, Fig. 9 presents a sensitivity analysis for the inventory variance ratio at the different echelons.

The main effect plots in Fig. 9a–c show that Info\_Shar and MA have the most important impact. Furthermore, the retailer’s inventory performance benefits from sharing the customer demand with the other partners in the supply chain, pushing toward collaboration to reduce the propagation of the bullwhip effect whilst keeping a satisfactory inventory variance in a win–win situation. The most significant effect at the retailer is due to the WD\_SS since it is able to recover quickly from instability when the wholesaler is holding much safety stock. Fig. 10 presents the impact of different stock levels throughout the supply chain.

Studying the inventory variance, it is possible to confirm all the results on the bullwhip effect, e.g. the importance of a higher MA and information sharing. The interaction between MA and the

safety stock levels of the upper echelons influences the inventory variance. Increasing the safety stock at echelon  $i$  leads to reduce the inventory variance at the downstream echelon  $i - 1$  and the decrease rate is higher if the echelon  $i - 1$  has a smaller level of safety stock.

The ANOVA results in Table 4 show the statistical significance of the above interactions.

5.3. Analysis of average service level sensitivity

As expected, the main effect plots in Fig. 11a–c show that the safety stock level has the most important impact on the average service level at all echelons. It is clear how increasing the safety stock at any echelon  $i$  increases the service level at that echelon and at the downstream echelons as well.

Fig. 12 details the impact of increasing the safety stock of the retailer on the average service level at the other echelons:

increasing the R\_SS level from 3.0 to 6.0 leads to increase the average service level at the retailer from 43% to 100% while the average service level at the wholesaler decreases from 45.3% to 40.8%, due to the amplification of the bullwhip effect and inventory variance ratio.

As well, all the other factors that contribute to increase visibility (information sharing and forecasting parameters) have a positive effect on the service level.

Fig. 11d–f shows that the most important interaction acts between the safety stock levels of the adjacent echelons. Increasing the safety stock level locally (e.g., at echelon  $i$ ) makes the average service level at that echelon insensitive to whatever the safety stock levels at the upstream echelons and especially echelon  $i + 1$ . Larger values of safety stock at an upstream echelon improves the average service level at the nearest downstream echelon, especially if the downstream echelon present a smaller safety stock. Furthermore, the interaction between the safety stock levels of

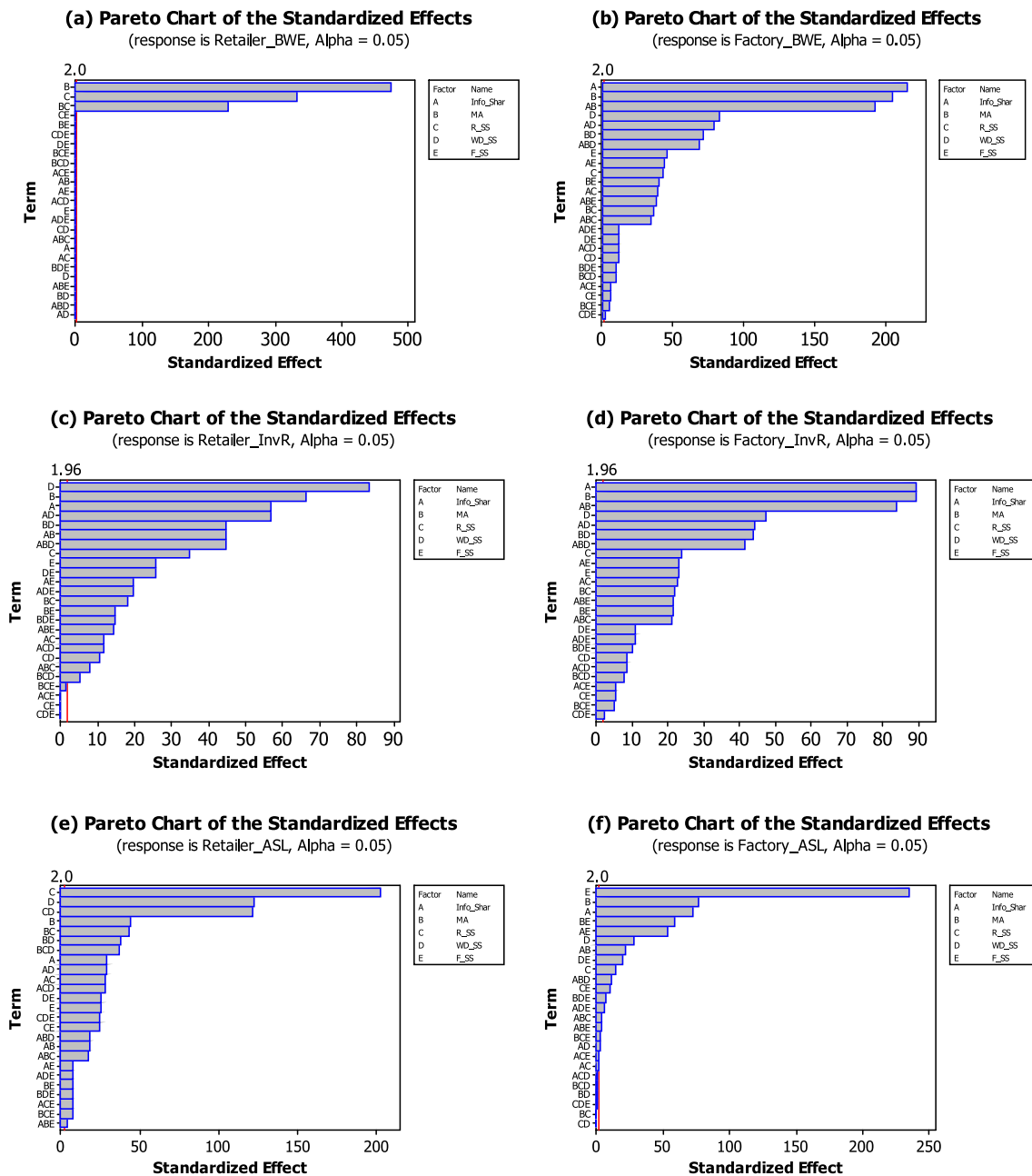


Fig. 13. The ranking of the most significant terms in the ANOVA model on the bullwhip effect (a and b), inventory variance (c and d), and average service level (e and f).



the distant upper echelons (e.g.  $i + 2$  and  $i + 3$ ) influences the average service level at echelon  $i$ .

The other interactions mainly show the role of safety stock in smoothing the impact of the operational parameters on the service level, helping to regulate the bullwhip effect and the supply chain instability. Table 5 shows the ANOVA results for the average service level.

## 6. Discussions and general implications

The scenario analysis and the experimental design provide a clear picture of the performances that a periodic review order-up-to level policy can generate in a supply chain. These results present many managerial implications with a natural extension to more complex system and real case applications. Three general principles combine the findings, summarizing the relative main and side effects.

### 6.1. Forecasting ability cannot substitute information sharing

Improving forecasting can help to reach effective results on the bullwhip effect ratio but sharing the value of the demand has a strongest impact on the overall performances. The ability of a supply chain partner to make accurate forecasts generates some improvement on its local performances that can be rapidly absorbed by the amplification of the bullwhip effect, if the other partners do not have the same capacity. The quantification of the inventory variance ratio and of the average service level shows that when the collaboration level increases, the performances improve to a great extent. The lack of visibility leads to a geometrical increase of the bullwhip effect and to a reduction of the average service level as moving upstream in the supply chain. The retailer, in contact with the customer, plays a key role: as owner of the demand information, it should be pushed to collaborate by the smoothing of the inventory variance due to the improvement of its supplier's service level. The same effect can also start at any level of the supply chain (sharing, for example, forecasts or orders time series) but, once the bullwhip effect triggers, the possibility of controlling performances is much limited.

### 6.2. Safety stock is not a synonymous of service level

The safety stock policy at the downstream echelons contributes to the level of instability at the upstream echelons. This simple result is as a good motivation for supply chain managers to seek for partnerships to restrict the propagation of information distortion.

Any coordination mechanism should provide the smallest safety stock level at the downstream echelons to achieve a target service level whilst protecting the upstream echelons from bullwhip propagation. This propagation might also lead to increase the inventory instability at the downstream echelons which means that there is a negative side effect in increasing the safety stock level: only a gradual adjustment of the safety stock across the supply chain (e.g.  $R_{SS} < WD_{SS} < F_{SS}$ ), whilst maintaining these levels as small as possible, suppresses the bullwhip effect amplification. Just in time policy are more effective when starting at the retailer, even without involving all the supply chain partners.

### 6.3. Coordination goes beyond information sharing

All the partners should select the appropriate value of the forecasting parameter to achieve order smoothing and overcome the inherent variability in incoming orders, allowing substantial benefits for both scenarios of traditional and information enriched supply chain. It helps to avoid the negative interactions that might happen: as shown in Fig. 13, the moving average parameter (MA),

information sharing (Info\_Shar) and their interactions give the highest contribution to the bullwhip effect and the inventory variance at the upstream echelon. Furthermore, these factors can act along with the safety stock level to improve the average service level. As information sharing level is high and moving average parameter is accurately selected, the bullwhip effect and the inventory variance tends to reduce and thus service level improves without the need for much safety stock. It is clear that optimizing supply chain is not an easy task especially in the absence of collaboration or information sharing. Supply chain performances not only depend on the local operational strategies but also on the coordination with other partners: in the above tables of ANOVA, 2-way and 3-way interactions have a statistical significance. Therefore, without collaboration, it is very hard to gain considerable improvements. These results provide a good motivation for initiatives such as VMI in which downstream echelons delegate the upstream echelons to replenish their inventories, eliminating layers of decision making.

## 7. Conclusions

The lack of coordination among supply chain partners affects their performances as a direct consequence of the bullwhip effect. This common statement derives from the operational causes of that generate distortion to the demand information, as for misalignments of forecasting techniques, ordering policies and safety stock levels. While many extensive researches quantified the impact of these causes under specific conditions, agreed by all the partners, this paper proposes a simulation study to analyze partial levels of collaboration. In particular, the simulation study presents the interactions that arise from different levels of information sharing and different choices in the inventory control parameters in a multi-echelon supply chain. The choice of the periodic review order-up-to level inventory control policy supports the extension and application of the findings to real cases where this policy commonly applies. The results confirmed the literature on the contribution of information sharing to the mitigation of the bullwhip effect, revealing how also inventory variance and average service level improves. The impact is most effective when the collaboration starts at the downstream echelons as, once the distortion of the demand starts, it is more difficult to limit and recover. The full factorial design examined the interactions among information sharing and the inventory control parameters to check to what extent they could interfere on the supply chain performances. While confirming the role of collaboration (e.g. demand sharing) in reducing the bullwhip effect, it was also clear how the coordination of the control policies, in term of forecasting and safety stock level at each echelon, can support service level by reducing the inventory variance. The general findings of the study showed that any decision, at each echelon, has an impact locally but also transmits its effect downstream and upstream, with the risk that expected benefits reduce without coordination.

The value of the study is to represent a methodology to give some insight about the relative contribution of the different decision leverage on the bullwhip effect and inventory stability. The attempt to quantify the performances of a multi-echelon supply chain with a periodic review order-up-to policy with moving average forecasting technique can be extended to evaluate the impact of the other operational causes of the bullwhip effect. Although many useful conclusions arose from this study, the impact of lead-times and order batching is a main stream of evolution, as well as other forecasting techniques. Therefore, further extension could cover different supply chain configurations with multiple nodes per echelon or applications of different inventory control policies. In particular, it would be beneficial to test the interactions of operational parameters and coordination on inventory control

policies that allow order smoothing through using control systems to fit the gap between target and actual inventory and supply line (Costantino et al., 2014b, 2014c). Following the relevant literature, this study restricts the allowance of negative customer demand and replenishment orders as a modeling assumption. Therefore, the effect of demand variation combined with the possibility of return policy (negative orders) should be studied to obtain useful insights for supply chains with returns allowance (Chatfield & Pritchard, 2013).

## Acknowledgements

The authors would like to thank the editors and two anonymous reviewers for their insightful comments and suggestions on an earlier version of this paper.

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