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Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains

Y Barlas[1]* and B Gunduz[2]

[1]Bogazici University, Istanbul, Turkey; and [2]Ford Otosan, Golcuk, Kocaeli, Turkey

Supply chain inventories are prone to fluctuations and instability. Known as the bullwhip effect, small variations in the end item demand create oscillations that amplify throughout the chain. By using system dynamics simulation, we investigate some of the structural sources of the bullwhip effect, and explore the effectiveness of information sharing to eliminate the undesirable fluctuations. Extensive simulation analysis is carried out on parameters of some standard ordering policies, as well as external demand and lead-time parameters. Simulation results show that (i) a major structural cause of the bullwhip effect is isolated demand forecasting performed at each echelon of the supply chain, and (ii) demand and forecast sharing strategies can significantly reduce the bullwhip effect, even though they cannot completely eliminate it. We specifically show how each policy is improved by demand and forecast sharing. Future research involves more advanced ordering and forecasting methods, modelling of other well-known sources of bullwhip, and more complex supply network structures.

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Introduction

Supply chain inventories are prone to fluctuations and instability. Small changes in the end item demand can create inventory and order oscillations that amplify as one moves up in the supply chain (Forrester, 1961, Chapter 12; Sterman, 1989; Sterman, 2000, Chapter 17, p 18). This phenomenon of amplification of oscillations through the supply chain is also known as the *bullwhip effect* (Lee *et al*, 1997; Chen *et al*, 1998; Xu *et al,* 2001).

Lee *et al* (1997) identifies four main causes of the bullwhip effect as: demand signal processing, order batching, rationing game, and price variations. Chen *et al* (1998) argues that the bullwhip effect is due, in part, to the need to forecast the demand. Sterman (2000, Chapter 17 and 18) and Forrester (1961, Chapter 12) show that delays inherent within the supply chain together with demand forecasting and distortion can create amplified oscillations.

Supply chain literature and management practice focus on coordination policies based on *information sharing* among supply chain members in order to reduce the bullwhip effect. Chen *et al* (1998) argues that centralizing demand information could significantly reduce the bullwhip effect. Xu *et al* (2001) and Lee and Whang (1998) report that sharing of the demand forecast and inventory information is effective in reducing order fluctuations and safety stocks. Gavirneni *et al* (1999) compares the no-information-sharing case against two different types of information-sharing policies used by the retailer (partial and complete sharing) in a simple one-retailer-one-supplier chain. Gallego and Özer (2001) searches optimal policies for with and without demand information-sharing cases in a two-stage supply chain, where the retailer batches orders and faces Poisson demands. Cheng and Wu (2005) show how information sharing can reduce inventory costs in a two-level chain with multiple retailers. Dejonckheere *et al* (2004) show that information sharing is very beneficial, if not indispensable in order-up-to-S policies since the magnitude of the bullwhip can thus be significantly reduced at higher levels in the chain. However, they note that information sharing cannot completely eliminate the bullwhip. Jeong and Maday (1996) discusses the stability of a multi-echelon supply chain from a feedback control theoretic perspective. Silver *et al* (1998) suggests demand sharing and *echelon inventory* policy implementations. Authors propose that each stage apply *echelon* (s, S) policy in which an agent monitors its total *echelon inventory* level. Chen *et al* (2000)

*Correspondence: *Y Barlas, Bogazici University, Department of Industrial Engineering, 34342, Bebek, Istanbul, Turkey.*
E-mail: ybarlas@boun.edu.tr

demonstrate the fact that smoother demand forecasts reduce the bullwhip effect, and longer lead times increase it. They also show that for both moving average and exponential smoothing forecasts, the very inclusion and need for estimation of a linear trend parameter into the forecasting model results in increased bullwhip. Dejonckheere *et al* (2002) analyze the effects of constant, linear, and quadratic exponential smoothing algorithms on the bullwhip. They show that the bullwhip emanating from the trend detection algorithms (linear and quadratic or exponential smoothing) are reduced by lowering the exponential smoothing constant used in these algorithms. More recently, Datta *et al* (2007) analyzes the relationships between demand and order forecasting and the bullwhip effect, and proposes an advanced forecasting model (GARCH) for supply chain management.

The purpose of our research is twofold: (1) to understand some of the underlying structures and factors that generate inventory fluctuations and the bullwhip effect through the supply chain; and (2) to explore the effectiveness of some management strategies in ameliorating this undesirable behaviour. We particularly focus on uncoordinated demand forecasting as a major cause of the bullwhip effect, and sharing of demand and forecast information as a counter-bullwhip management policy. System Dynamics modelling is used as the research platform.

The model structure

We consider a three-stage supply chain system consisting of identical agents where each agent orders only from its upper agent $(i+1)$. An agent ships goods immediately upon receiving the order, if there is sufficient on-hand inventory. Orders may be partially fulfilled, and unfulfilled orders are backlogged. Shipped goods arrive after a constant transit lead time (LT). The model represents a general un-capacitated producer-wholesaler-retailer setting. The uppermost stage (producer) places orders to an unlimited source, so there is no backlogging of the producer orders by the raw material/parts supplier. Alternatively, we can think of a factory that always keeps enough stock of raw material and parts. This assumption is made in a sense to draw a practical model boundary, else the same inventory management structure would have to be cascaded too many times, without adding any conceptual or novel dimension to the research. (See the stock-flow diagrams and equations below.)

For consistency with models and policies in the inventory literature, time is modelled discrete (DT = 1 time period). This makes the model time-discrete that is necessary to represent standard ordering policies like Order-up-to-S and (s, S), as will be described below. Another policy analyzed, the anchor-and-adjust ordering rule typically used in system dynamics models, is normally time-continuous. As will be explained below, in the assumed parameter settings, it was possible to represent the anchor-and-adjust ordering rule with DT = 1 as well, without causing any erroneous dynamics.

The basic generic equations of the model are described in this section (except the policy-specific ordering equations that are presented later in separate sections).

Local inventory (LI) increases with arrivals and decreases with shipments:

$$LI_{i,t} = LI_{i,t-1} + (A_{i,t} - S_{i,t}) \quad \text{[Goods]} \qquad (1)$$

where $A_{i,t}$ is the arrivals to stage i and $S_{i,t}$ is the shipments from stage i in period t.

In transit inventory, the goods shipped by the upper stage that have not yet arrived:

$$IT_{i,t} = IT_{i,t-1} + (S_{i+1,t} - A_{i,t}) \quad \text{[Goods]} \qquad (2)$$

Goods in transit arrive after an exponential (gradual) delay structure:

$$A_{i,t} = IT_{i,t}/LT_i \quad \text{[Goods/Period]} \qquad (3)$$

where LT_i is the transit lead time needed for shipments by stage $(i+1)$ to reach stage i.

Shipment requirement (SR) for a stage i is the sum of demand faced ($D_{i,t}$) at time t and backlogged orders ($BL_{i,t}$):

$$SR_{i,t} = BL_{i,t} + D_{i,t} \quad \text{[Goods/Period]} \qquad (4)$$

If there is enough LI, the required amount is shipped immediately in one period. If not, the unfulfilled portion of orders is added to BL:

$$S_{i,t} = \min(SR_{i,t}, LI_{i,t}) \quad \text{[Goods/Period]} \qquad (5)$$

$$BL_{i,t+1} = BL_{i,t} + D_{i,t} - S_{i,t} \quad \text{[Goods]} \qquad (6)$$

Net inventory (NI) is the LI after the backlogged orders are subtracted:

$$NI_{i,t} = LI_{i,t} - BL_{i,t} \quad \text{[Goods]} \qquad (7)$$

Agents are assumed to be unaware of the exact demand pattern they are facing, so they must forecast the future demand. Simple exponential smoothing is used as the forecasting mechanism. Thus, the expected demand is calculated by:

$$E_{i,t} = E_{i,t-1} + (1/EAT_i)(D_{i,t-1} - E_{i,t-1}) \quad \text{[Goods / Period]} \qquad (8)$$

where EAT_i is the expectation adjustment time used by stage i. $D_{i,t-1}$ is the demand faced by stage i. The end demand D_1 is an external input to be described in the next section and demands D_2 and D_3 faced by stage two and three are actually the orders placed by their lower stages. ($D_i = O_{i-1}$, where O_i are to be described in the following sections.)

For any agent, the total expected demand during LT ($\hat{D}_{i,L}$) is simply calculated by the expected demand for one period multiplied by LT:

$$\hat{D}_{i,L} = (LT_i)(E_{i,t}) \qquad \text{[Goods]} \qquad (9)$$

Each agent continuously monitors her inventory position (IP), defined as the sum of her local inventory (LI), in transit goods (IT) from the upper stage, backlog (BL) at the upper stage, minus BL at her own stage:

$$IP_i = LI_i + IT_i + BL_{i+1} - BL_i \qquad \text{[Goods]} \qquad (10)$$

In real life, it is difficult for an agent to know how much of its orders are in transit and how much are backlogged by the upper stage. So, the explicit inclusion of the term 'orders backlogged by the upper stage ($BL_{i+1,t}$)' in the IP formulation may seem too idealistic. However, all ordering policies tested in this research utilize the *sum* of in-transit goods and upper stage backlogs ($IT_i + BL_{i+1}$), which is simply the difference between the total orders given and the ones that have arrived. An agent does not need to obtain specific BL information from its upper stage in order to determine total orders that have not yet arrived ($IT_{i,\ t} + BL_{i+1,\ t}$). Thus, the above formulation does not imply an unrealistic assumption in a real application.

The stock-flow diagrams for retailer, wholesaler, and producer are shown in Figure 1 and 2.

The demand pattern

Three types of demand input are used: (1) deterministic 'step up and down' demand for testing/verification purposes; (2) iid random demand (Normal (20,2)) in some selected comparison runs; and (3) stationary autocorrelated demand (obtained by exponential smoothing of white noise, with an autocorrelation period of five) used in most runs in this paper, unless otherwise noted. (Figure 3 illustrates these three demand patterns.)

Ordering policies

Three basic inventory management policies are tested within the supply chain model: Order-up-to-S policy, a standard system dynamics ordering policy (anchor-and-adjust

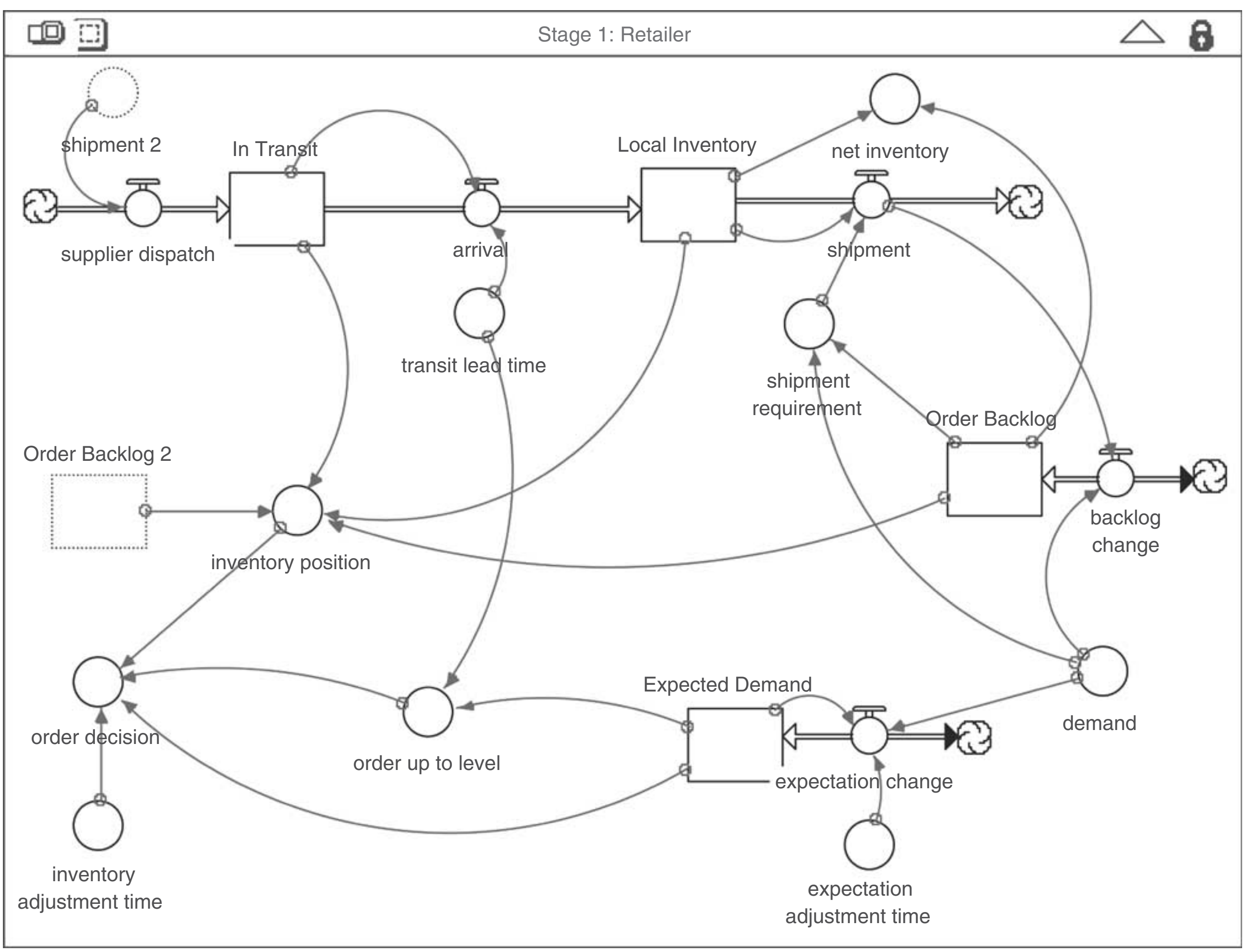

Figure 1 General stock-flow diagram of the supply-chain model: stage one, retailer.

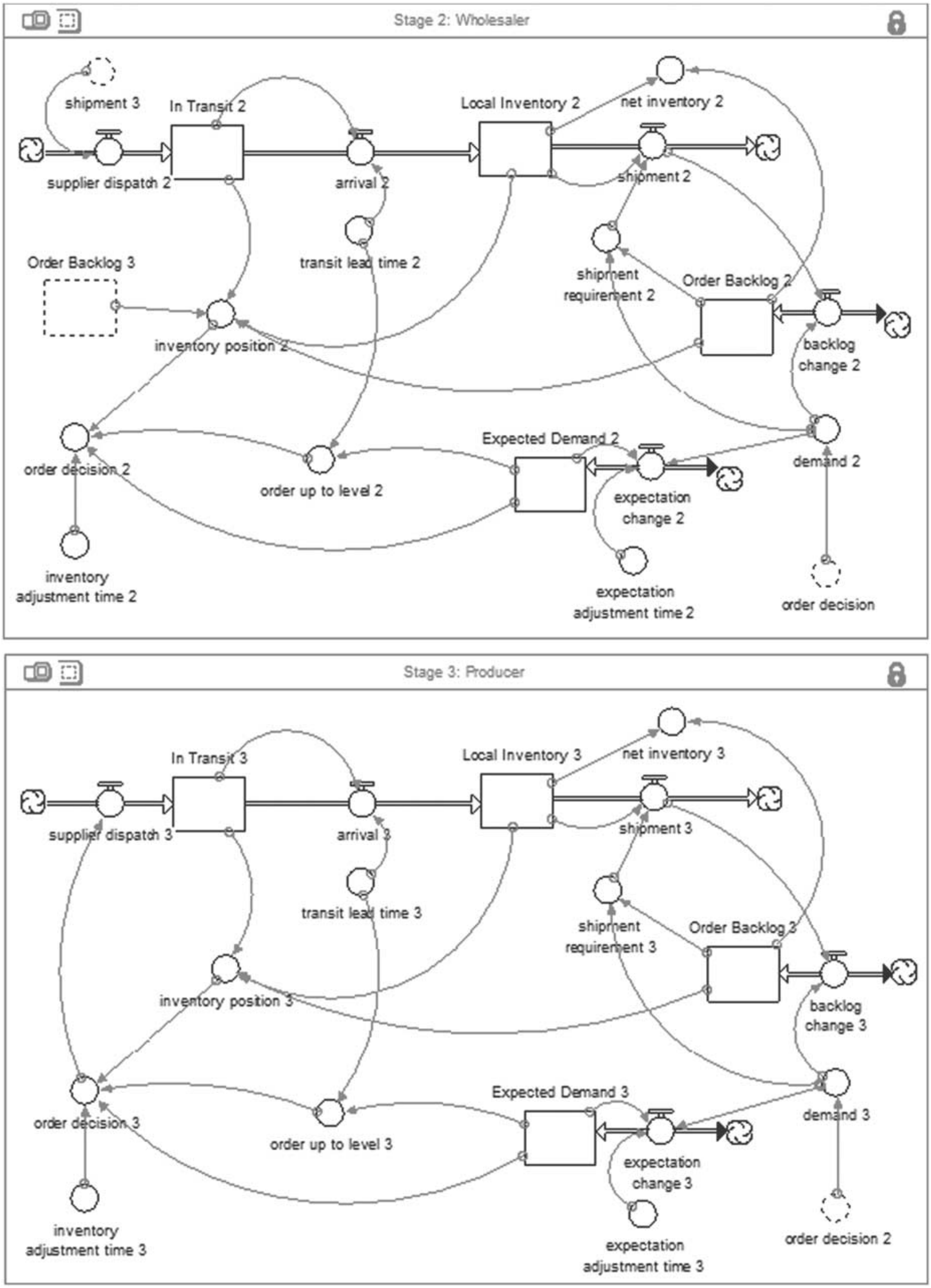

Figure 2 Stock-flow diagram of stage two and three: wholesaler and producer.

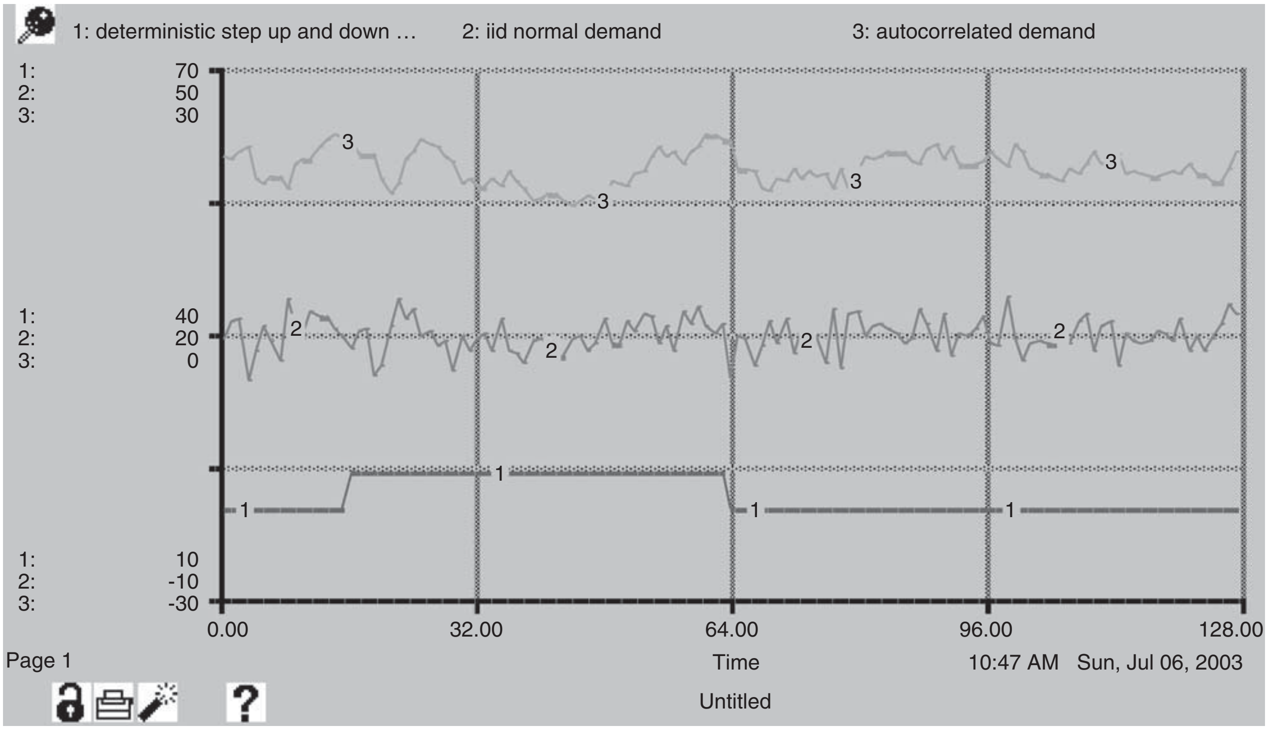

Figure 3 Three different demand patterns used in simulation experiments.

policy), and (s,S) policy. All stages are assumed identical, so for each tested policy all stages use the same policy with the same parameters. In reference runs, each stage locally decides on the order quantity *without* considering the overall supply chain.

Order-up-to-S policy

Order-up-to-S policy is the well-known base-stock policy where an agent orders the quantity needed to bring its IP up to a base-stock level S, whenever it falls below S. The associated ordering equation is:

$$O_{i,t} = \max\left((S_{i,t} - IP_{i,t})/IAT_i, 0\right) \quad \text{[Goods/Period]} \tag{11}$$

Where $O_{i,t}$ is the order decision, $S_{i,t}$ is the order-up-to-level, $IP_{i,t}$ is the inventory position, and IAT_i is the inventory adjustment time. In the standard order-up-to-S policy, the discrepancy is immediately ordered, so we set inventory adjustment time (IAT) to one.

The order-up-to-level ($S_{i,t}$) can be set in different ways. One approach is to compute it by $S = \hat{D}_L + k\sigma_L$, where $\hat{D}_L$ is expected demand during LT, $k\sigma_L$ is safety stock where σ_L is the standard deviation of forecast errors of LT demand, and k is a constant selected according to desired service level. In any case, the idea is to set S at a level greater than $\hat{D}_L$ to account for demand variation (See Gündüz, 2003). Another practical formula suggested for S is to 'inflate' the shipment LT by a factor K, to account for demand variation. Thus, the formula is:

$$S_{i,t} = (LT_i + K_i)E_{i,t} \quad \text{[Goods]} \tag{12}$$

where LT_i is the transit LT for stage i, K_i is the 'lead time inflation constant', and $E_{i,t}$ is the expected demand (or expected orders from stage $i-1$) estimated by stage i. (Recall that $\hat{D}_{i,L} = (LT_i)(E_{i,t})$ anyway, so that the term $(K_i)E_{i,}$ is the extra addition to $\hat{D}_L$ to account for random variation.)

In this policy, the order-up-to-level S is updated each period, as the expected demand is updated. The resulting inventory dynamics (with autocorrelated demand), $LT_i = 3$, $K_i = 2$ is seen in Figure 4. Note the oscillations and the bullwhip effect (amplification) along the supply chain, as one moves from the retail end toward the producer. The increase in the bands of fluctuations as we move up in the supply chain is graphically indicated more clearly in Figure 5.

System dynamics anchor-and-adjust policy

This is the anchor-and-adjust policy widely used in System Dynamics literature (Sterman, 2000; Barlas, 2002). This policy tries to stabilize LI at a desired level. The associated order equation is the following:

$$O_{i,t} = \max\left((I^*_{i,t} - I_{i,t})/IAT_i + (SL^*_{i,t} - SL_{i,t})/SLAT_i + E_{i,t}, 0\right) \quad \text{[Goods/Period]} \tag{13}$$

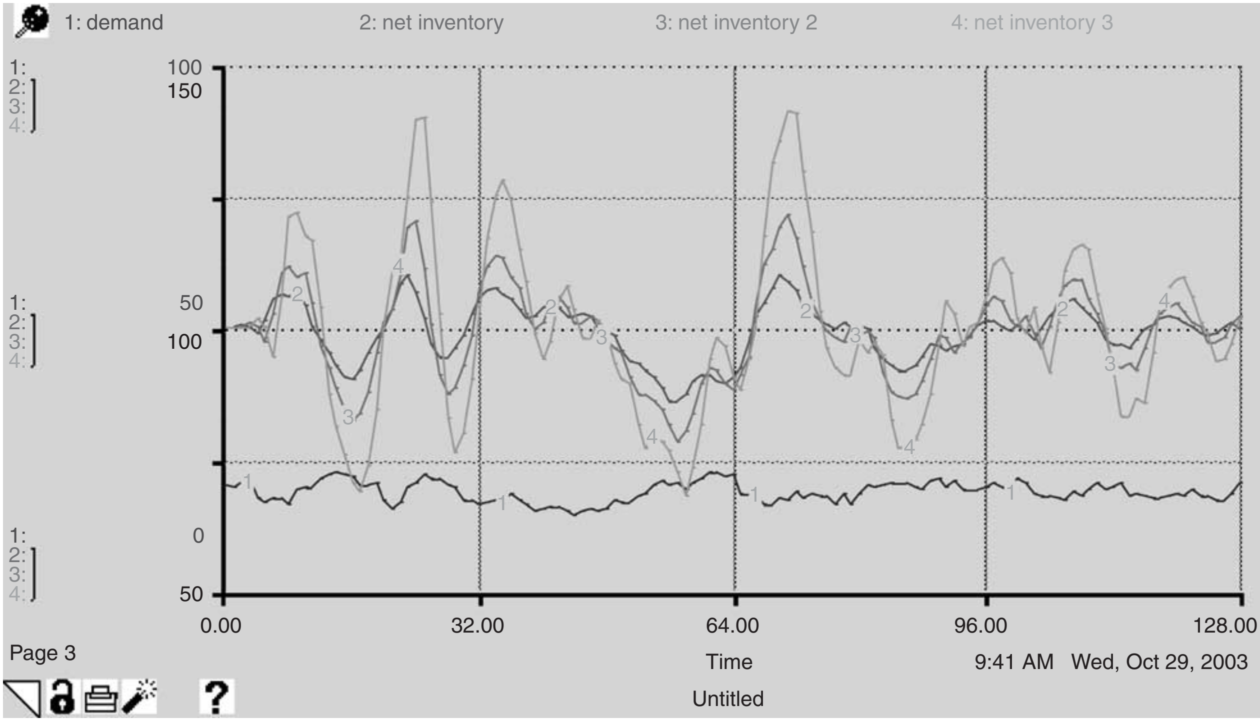

Figure 4 Net inventories when order-up-to-S policy is applied (2: retail; 3:wholesaler; 4: producer).

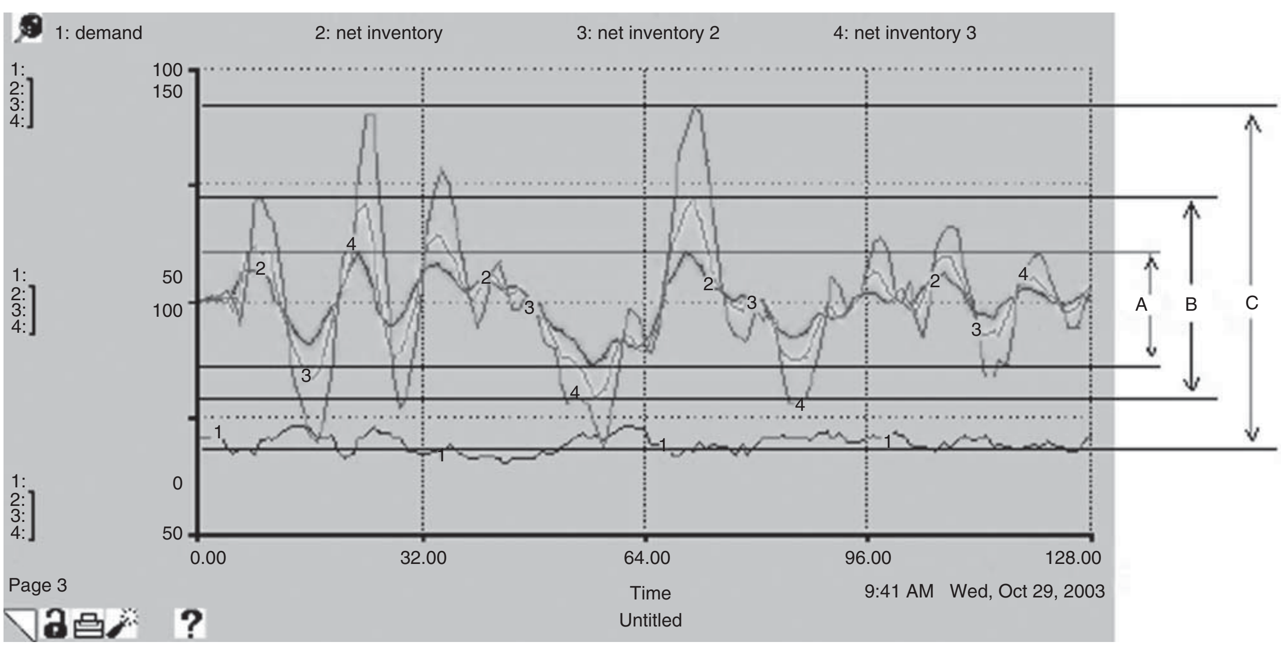

Figure 5 The bullwhip effect: the bands of inventory fluctuations are amplified as one moves from the retail end to the wholesaler, and then to the producer end (marked by A, B, and C respectively).

where $I^*_{i,t}$ is the desired inventory level and $SL^*_{i,t}$ is the desired supply line, IAT and $SLAT$ are inventory adjustment time and supply line adjustment time, respectively.

$I_{i,t}$ and $SL_{i,t}$ represent inventory level and supply line that are defined as follows:

$$I_{i,t} = LI_{i,t} - BL_{i,t} \qquad \text{[Goods]} \tag{14}$$

$$SL_{i,t} = IT_{i,t} + BL_{i+1,t} \qquad \text{[Goods]} \qquad (15)$$

The desired levels of inventory and supply line are typically determined by:

$$SL^*_{i,t} = LT_i \times E_{i,t} \quad \text{[Goods]} \qquad (16)$$

$$I^*_{i,t} = M \qquad \text{[Goods]} \qquad (17)$$

where M is some chosen constant.
Note that in this policy, the desired supply line $SL^*_i, _t$ is adjusted according to the expected demand, so as to yield an arrival rate equal to the expected demand at equilibrium. The desired inventory level on the other hand is taken as constant in the simplest version of the policy.

Inventory behaviour in this case (with autocorrelated demand, $M = 100$, $LT = 3$, and $IAT_i = SLAT_i = 1$) is seen in Figure 6. Just like with the order-up-to-level S policy, we observe oscillations and the bullwhip effect (amplification) through the supply chain, from the retailer to the wholesaler and then to the producer. (Comparing Figures 4 and 6, also note that the behaviour patterns of orders and inventories with order-up-to-S policy and anchor-and-adjust system dynamics policy are quite similar.) As an alternative, the desired inventory in the adjustment equation above can be defined as proportional to the expected demand, namely $mE_{i,t}$. With this formulation, both the oscillation amplitudes and the bullwhip effect increase as a result of stronger (double) effect of the expected demand on orders. We are unable to provide the corresponding graphs due to space limitation (the reader is referred to Gündüz, 2003).

Finally note that, as explained before, for comparison and consistency between all policies, the anchor-and-adjust policy runs reported in this article are done with $DT = 1$ (ie with a discrete model). Since system dynamics models are typically continuous, we have also tested the model with several smaller DT values to make sure that the obtained behaviours are not sensitive to DT. Indeed, very similar inventory oscillations and bullwhip effects were obtained with smaller DT values, proving that the results are not sensitive to $DT = 1$. (We are unable to provide the graphs due to space restrictions; please see Gündüz, 2003.)

(s,S) Policy

(s,S) Policy is a review policy where orders are placed to raise IP to order-up-to-level S, whenever IP drops to the reorder point s or below. The order equation is as follows:

$$O_{i,t} = (S - IP_{i,t})/IAT \qquad \text{if } IP_{i,t} \leqslant s$$
$$O_{i,t} = 0 \qquad \text{otherwise} \quad \text{[Goods/Period]} \qquad (18)$$

In the standard (s,S) policy, the discrepancy is immediately ordered, so we set IAT to one. The parameters s and S must typically be determined as functions of LT and the expected demand E. In general, the larger LT and E, the higher must be the reorder point s, due to a riskier situation. Similarly, the larger E, the higher must be the

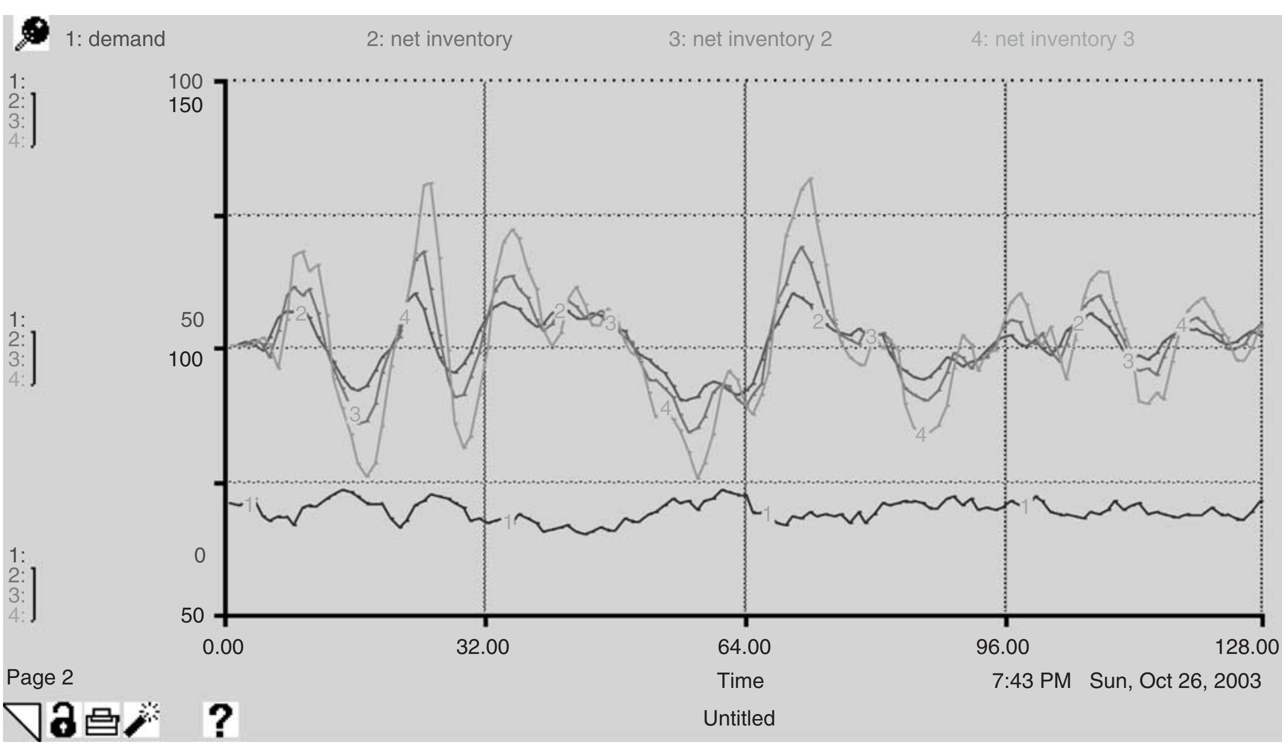

Figure 6 Net inventories when 'anchor and adjust' policy is applied.

order-up-to-level S in order to prevent frequent shortages. Thus, even if we assume constant LT, s and S must be updated in practice, since the demand (hence E_t) would be varying in time. In light of this, the reorder point $s_{i,\,t,}$ and the order-up-to-level $S_{i,\,t}$ for stage i at time t, can be computed by the following equations:

$$s_{i,t} = (LT_i)(E_{i,t}) + SS_i \qquad \text{[Goods]} \tag{19}$$

$$S_{i,t} = s_{i,t} + q\,E_{i,t} \qquad \text{[Goods]} \tag{20}$$

where SS_i is some safety stock that must be kept by the company, and q is a constant order multiplier to provide a buffer for the variation in demand. (S could also be determined by $s+\text{EOQ}$, where EOQ the optimal 'economic order quantity' to be calculated for given inventory holding and BL costs. Optimal computations of s and S are extremely difficult and irrelevant to the purpose of this article—see for instance Nahmias, S. (2009, Chapter 5)). Since it is known in general that EOQ is an increasing function of estimated demand $E_{i,\,t,}$ using $q\ E_{i,\,t}$ in lieu of EOQ is reasonable. The inventory dynamics with LT = 3, SS = 240 and $q = 3$ is shown in Figure 7. Once again, we observe oscillations and the bullwhip effect along the supply chain. Note further that the level of amplification in this case is stronger than the previous two cases—the amplitude of oscillations more than doubles with each stage. As will be analyzed later, this finding is consistent with the Lee *et al* (1997) results that 'order batching' together with demand forecasting is one of the main causes of the bullwhip effect. In (s,S) policy, orders are in effect batched.

A related issue would be the frequency of updating s and S. The above formulas assume that s and S are updated in every period t. It is likely that in some situations, s and S are updated less frequently, especially if the demand tends to change slowly. Another extreme would be not to update s and S at all through the entire simulation horizon. In this article we also present this extreme case of keeping s and S constant through the entire horizon, in the *Policy Analysis* section below.

Analysis of the sources of the bullwhip effect

Numerous simulation experiments are carried out using each of the three ordering policies described above. (Some variants of these policies and other policies like (s,Q) have been tested as well, but we skip them due to space limitations (see Gündüz, 2003)). These experiments can be grouped in two: policy-independent parameters of the supply chain and policy-specific parameters.

Policy-independent parameter analysis

Simulation experiments are performed with different settings of demand pattern (autocorrelation degree), LT, nature of delays, and demand estimation adjustment time (EAT). Some important results can be summarized as

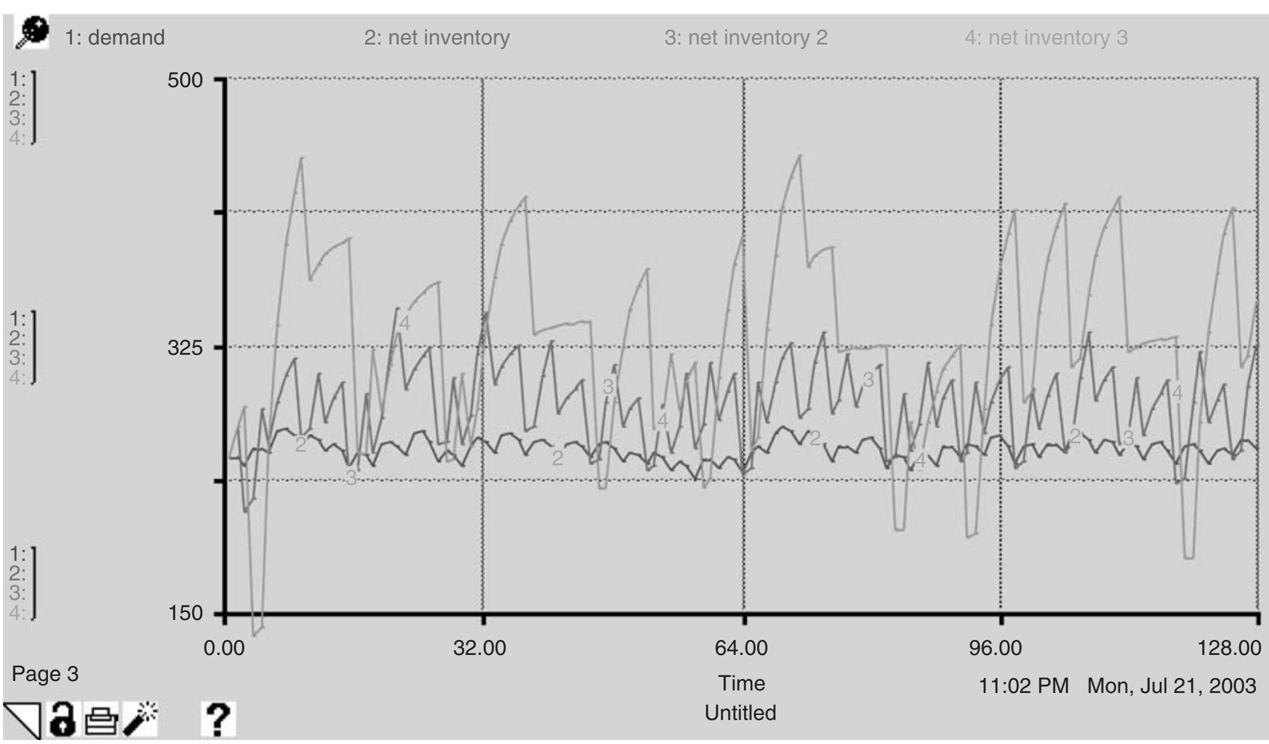

Figure 7 Net inventories when (s,S) policy is applied (SS = 240, $q = 3$).

follows. Only one example behaviour graph is shown due to space limitation (See Gündüz, 2003).

- If the end item demand is *autocorrelated*, the base (retail) oscillations and the bullwhip effect both increase, especially when order-up-to-S policy or anchor-and-adjust policy is used. With (s,S) policy, autocorrelation does not have substantial effect on inventory oscillations, because significant 'batching' of orders in (s,S) makes it insensitive to demand autocorrelation. But this batching has a bullwhip effect as will be seen later.
- The bullwhip effect increases with an increase in LT. This is essentially caused by the fact that the up-to-order level S and the desired supply line $SL^{*}_{i,t}$ are both proportional to LT (delay). The orders and the resulting inventory oscillations are, hence, amplified. The same is not true with (s,S) policy, where the order quantity and the frequency are not affected by LT.
- In the basic model, the only delay is the material delay on the supply line ('lead time'). In reality, there can be other delays like *information delay* in placing orders. The effects of including such additional delays in the ordering mechanisms have been investigated. In all three policies, the bullwhip effect significantly increases with inclusion of order information delays (see Gündüz, 2003). This is consistent with our above result about the bullwhip effects of increased LT, since additional information delays effectively increase LT in receiving the orders placed.
- Base retail oscillations and bullwhip both *decrease* significantly with an increase in the demand EAT, for all three policies. (Compare Figure 8 below, with Figure 4 above, as an illustration.) The explanation is that, the larger EAT, the *less* responsive the model becomes to changes in demand (or incoming orders). Since uncoordinated demand forecasting is a main cause of the bullwhip effect (Lee *et al* 1997), larger EAT, meaning less responsive (or almost 'no') forecasts, naturally lead to decreased bullwhip effect. This result is important in the sense that it reveals one of the major causes of the bullwhip phenomena: uncoordinated demand forecasting, as will be discussed below.

Table 1 summarizes for each ordering policy, the effects of four policy-independent parameters on oscillations and bullwhip, as discussed in this section.

Policy-specific parameter analysis

In the second set of runs, we experiment with policy-dependent parameters such as LT inflation constant K in the order-up-to-S policy, order quantity multiplier q in (s,S) policy, and the desired inventory coverage constant m in the anchor and adjust policy. (See the associated equations of each policy, above.)

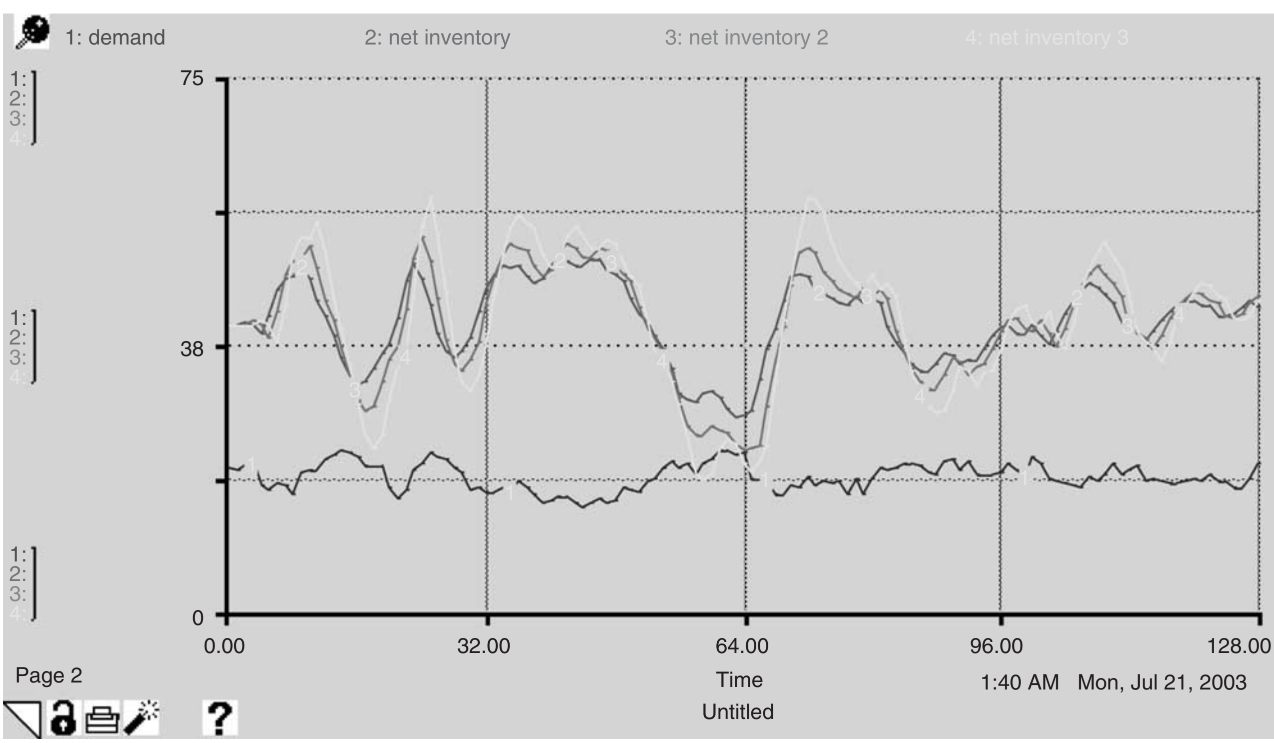

Figure 8 Net inventories with order-up-to-S policy and EAT increased to 10.

Table 1 Summary of policy-independent parameter analysis

Parameter change: Policy	*Demand pattern (from iid normal, to autocorrelated)*	*Increase in lead time (from 3 to 6)*	*Inclusion of order information delay*	*Increase in estimation adjustment time (from 5 to 10)*
Order-up-to-S Policy	Oscillations and bullwhip effect increase	Bullwhip effect increases	Bullwhip effect significantly increases	Oscillations and bullwhip effect significantly decrease
System Dynamics Anchor-and-Adjust Policy	Oscillations and bullwhip effect increase	Bullwhip effect increases	Bullwhip effect significantly increases	Oscillations and bullwhip effect significantly decrease
(s,S) Policy	No substantial change in behaviour	No substantial change in behaviour	Bullwhip effect significantly increases	Oscillations and bullwhip effect significantly decrease

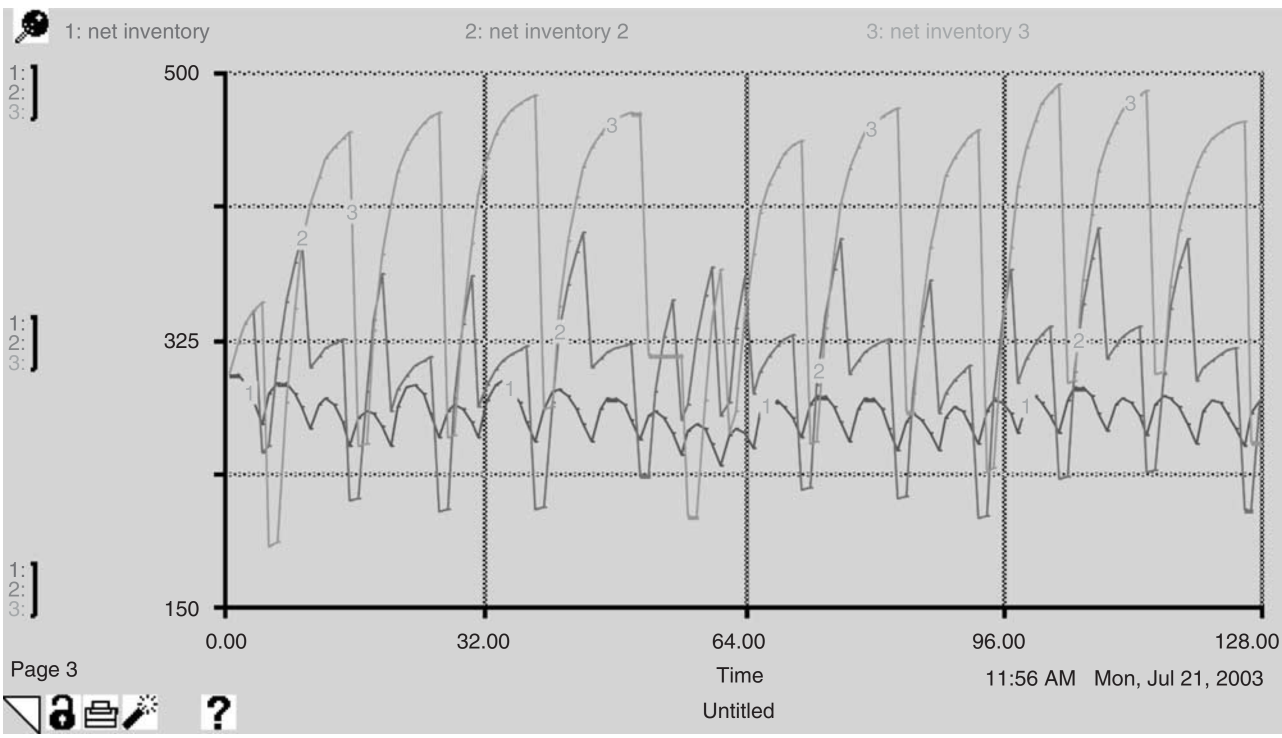

Figure 9 Net inventories when (s,S) policy is applied (SS = 240, $q = 5$).

- Experiments show that when LT inflation constant K (in the order-up-to-S policy) is increased, the bullwhip effect also increases. (We are unable to show the graphs due to space limitations; see Gündüz, 2003.) Note that K is a multiplier of the expected demand in the order-up-to-level computation in this policy; so it represents the weight of the expected demand in the order decisions.
- When the order quantity multiplier q (in (s,S) policy) is increased, the bullwhip effect and magnitude of oscillations both increase (compare Figures 9 and 7). Note again that q is a multiplier of the expected demand in the order-up-to-level S formula in this policy; it represents the strength of the demand forecast in the order decisions.
- When the desired inventory coverage constant m (in the anchor and adjust policy) is increased, the bullwhip effect and magnitude of oscillations both increase (See Gündüz, 2003 for output graphs). Observe that in this policy, the desired inventory is obtained by multiplying the demand forecasts with the coverage constant m, so that the latter represents again the weight of demand expectations in order decisions.

Table 2 summarizes the effects of the parameters of each ordering policy, on oscillations and bullwhip, as discussed in this section.

All the three policy-specific results point to a single general result. The stronger the role of isolated demand

Table 2 Summary of policy-specific parameter analysis

Parameter change: Policy	*Increase in lead time inflation constant K (from 1 to 3)*	*Order quantity multiplier q (from 3 to 5)*	*Desired inventory coverage constant m (from 3 to 5)*
Order-up-to-S policy	Bullwhip effect increases		
System dynamics anchor-and-adjust policy			Bullwhip effect and magnitude of oscillations increase
(s,S) policy		Bullwhip effect and magnitude of oscillations increase	

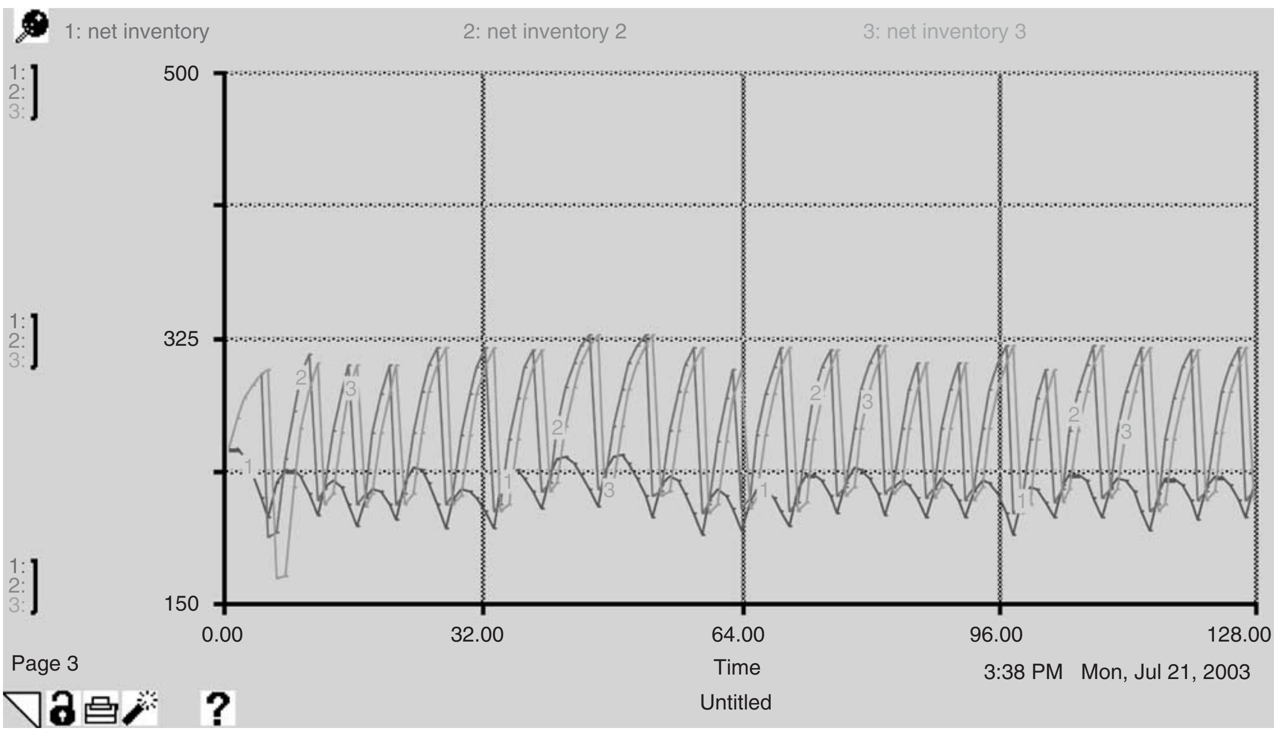

Figure 10 Net inventories under (s,S) policy, without using any forecasting.

forecasts in the order decisions, the stronger is the bullwhip effect (and in some cases the base retail oscillations). This result is consistent with Forrester (1961), Sterman (2000), Yaşarcan and Barlas (2005), Barlas and Özevin (2004), Lee *et al* (1997), and Chen *et al* (1998). This finding, together with the earlier result about the role of order batching in amplifying the bullwhip effect, leads to two important policy-oriented roots of the bullwhip.

The role of order batching

Among the policies tested, orders are batched in the (s,S) policy, since they are not placed in each period. We noted earlier that the effect of this batching is an increase in the bullwhip effect, comparing the larger amplifications in Figure 7 with those in Figures 4 and 6. But the other major cause of the bullwhip, ie demand/order forecasting, is also present in these (s,S) policy runs. In order to isolate and focus on the effect of order batching *only*, we test (s,S) policy with *fixed* levels of *s* and *S* that are *not* updated by any demand/order forecasts. Results in this case (Figure 10, compared to Figure 7) reveal that when demand forecasts are not used, under the effect of order batching only, the bullwhip does *not* propagate through the entire chain, it occurs from the retailer to the wholesaler only. The amplification from the retailer to the wholesaler is a result of batched orders, so the wholesaler faces batched orders while the retailer faces un-batched retail demand. There is no amplification at all from the wholesaler to the producer, because both of these agents face the same type of batched orders, with the same ordering rules. The same would be true from any stage n to stage $n+1$, $n>1$). Thus, we conclude that the batching of orders by itself is *not* sufficient for the bullwhip effect to propagate in the supply chain; order policy parameters must be updated by demand forecasts for the bullwhip to propagate. But we also conclude that batching *can* further amplify the bullwhip effect, if the latter already exists as a result of demand/order forecasts. Finally, note that if agents used higher and higher degrees of batching (ie less frequent orders) as we upstream, then order batching could by itself result in bullwhip effects that would propagate through the entire chain, even without any demand forecasting. Such detailed analysis of the specifics of different ordering policies is beyond the scope of this article. For instance, Potter and Disney (2006) show that in (S, nQ) policy, the bullwhip effect is reduced if the batch size Q is a multiple of average demand, and in-between the minima, the bullwhip effect rises and falls in a waveform, reaching a peak at the halfway point.

The role of demand/order forecasting

Analysis of the simulation results of no-demand-sharing cases reveals that a primary cause of the bullwhip effect is the isolated sequential demand forecasting performed at each stage of the supply chain, making use of previous stage's orders. This result is also supported by Lee *et al* (1997), Chen *et al* (1998), Sterman (2000, Chapter 17 and 18), and Forrester (1961, Chapter 12). As we have seen above, the weight of demand forecasts in ordering decisions determines the degree of the bullwhip experienced by the chain. All ordering policies that use demand forecasts in ordering equations multiply demand forecasts by a constant in order to obtain some 'target' order level. This constant is K for order-up-to-S policy, m for anchor-and-adjust policy, and q for (s,S) policy (see equations above). Simulation runs show that the higher is the multiplier constant, the greater is the magnitude of the bullwhip effect (see Figure 9 for example, for the (s,S) policy case).

Experiments with different EAT values also reveal that the bullwhip effect decreases with an increase in EAT (Figure 8). Increase in EAT means that demand forecasts are *less* responsive to changes in demand. A very high EAT effectively means no forecast updating, yielding 'almost constant' demand forecasts. At the extreme, constant ('no') demand forecasting results in zero bullwhip effect (Figure 10 for example). Note that this last extreme result is of theoretical value, but would not be implementable in real world. Inventory management without any demand forecasting would obviously cause major problems in terms of shortages and over stocking, so eliminating the bullwhip effect would not be of much practical value with such a strategy.

Improved policy: demand and forecast information sharing

There are several strategies suggested in the literature to tackle the bullwhip effect, as summarized in the introduction. One such strategy, also implied by our results, is sharing of demand and/or forecast information between agents in the supply chain. There is a rich literature arguing for demand/forecast information sharing, some of which was mentioned above in the *Introduction* section. In order to explore the effects of this strategy on the behaviour of the inventories, we modify the supply chain model to incorporate end-item demand sharing. Each stage uses end-item demand information to forecast the future demand, rather than using orders of its lower stage. Hence, all stages use demand forecasts obtained directly from end-item demand in their ordering decisions. In the base case reported here, since all agents in the model use the same forecasting mechanism with same parameters, end-item demand sharing is equivalent to demand forecasts sharing. Given that the end item demand is shared, all stages effectively produce and use the same end item demand forecasts. (If agents used different forecasting methods, then demand sharing and forecast sharing would be two different strategies.)

The resulting inventory behaviours for order-up-to-S policy, SD policy, and (s,S) policy when demand is shared are shown in Figures 11–13 respectively. Demand and forecast sharing eliminates uncoordinated sequential forecasting mechanisms of the supply chain so that a stage no longer bases its orders on its forecasts of the lower stage's orders. Instead, each stage directly uses end-item forecasts. Thus, the bullwhip effect along the supply chain is significantly reduced. (Compare Figure 11 to Figure 4; Figure 12 to Figure 6; and Figure 13 to Figure 7.) Our results are consistent with experimental and empirical evidence on the role of demand information sharing on stabilizing supply chain inventories (for instance, Chen *et al,* 1998; Cheng and Wu, 2005; Croson and Donohue, 2005).

Order-up-to-S policy

Anchor and adjust policy

(s,S) policy

Another strategy suggested against bullwhip is the *echelon* inventory policy, where each agent places orders based on echelon IP rather that its local position. The echelon inventory of a stage is defined as IP of the subsystem consisting of the stage itself and all its downstream stages (see Silver *et al*, 1998). When the model is run with Echelon policies, we obtain a further decrease in the bullwhip effect because these policies remove the order propagation delay

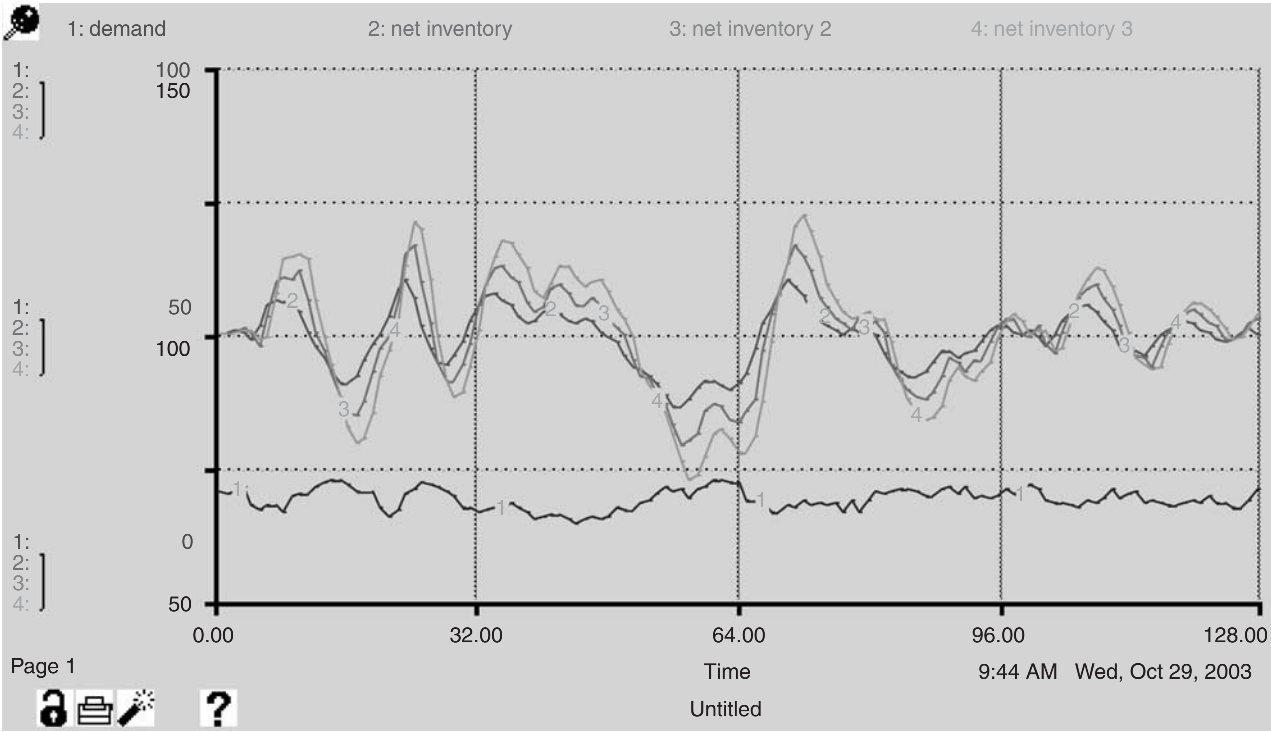

Figure 11 Net inventories when order up-to-S policy is applied and demand is shared.

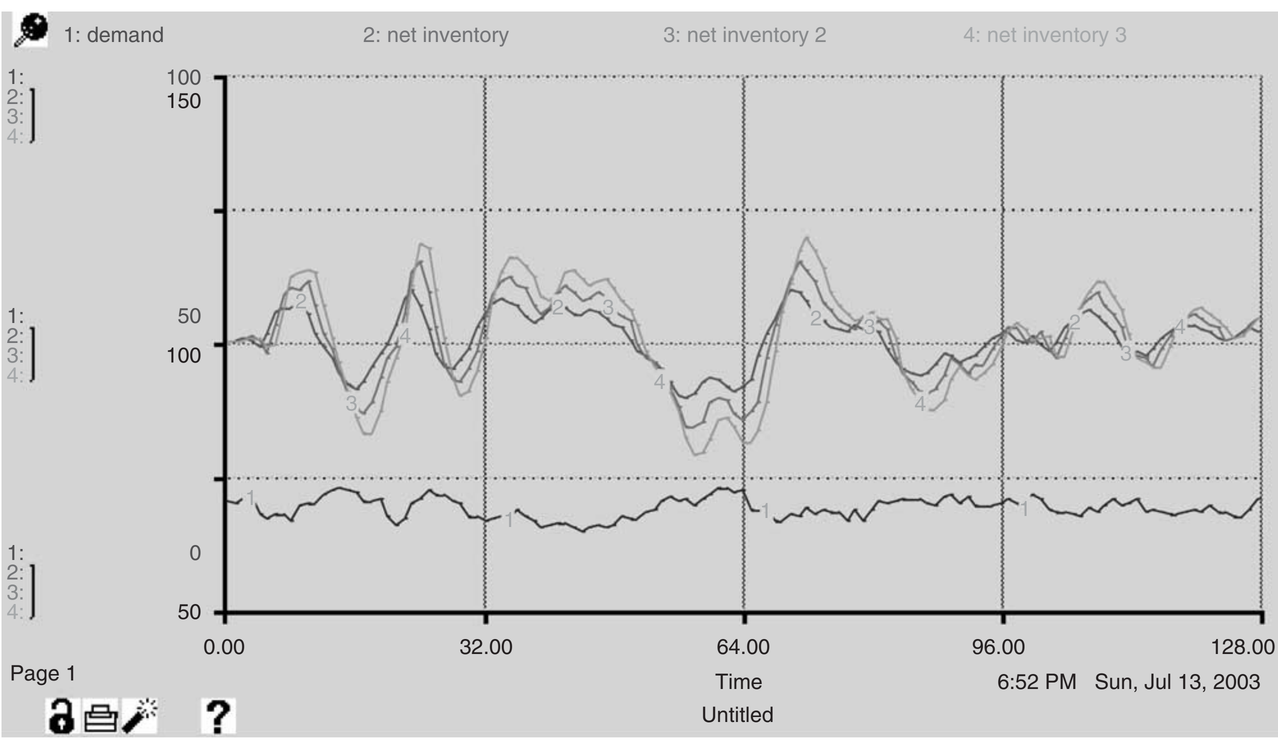

Figure 12 Net inventories when anchor and adjust policy is applied and demand is shared.

from the supply chain. (We are unable to provide output graphs and further discussion of echelon policies due to space limitations (see Gündüz, 2003)).

Table 3 summarizes the consequences of the demand forecasting/sharing and the Echelon inventory policies vis-a-vis the bullwhip effect.

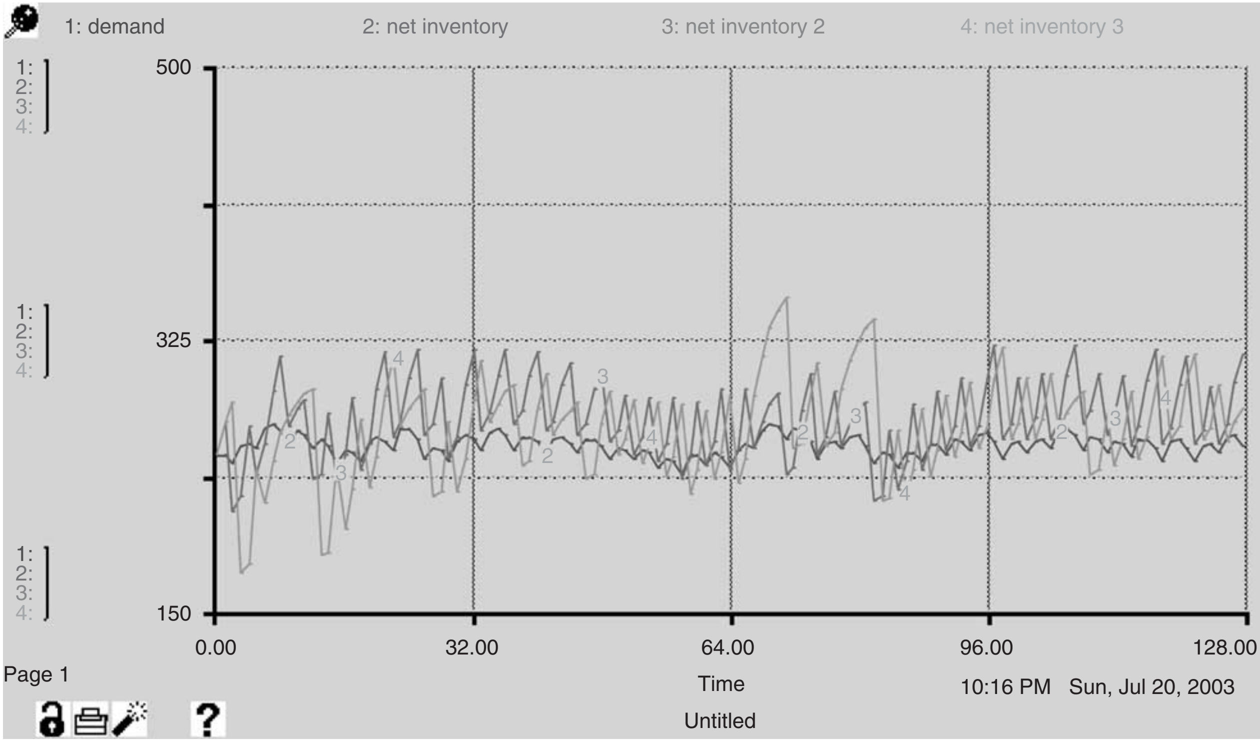

Figure 13 Net inventories when (s,S) policy is applied and demand is shared.

Table 3 Summary results of information-sharing policies

Scenario:	*No demand forecast is employed*	*Demand and forecast sharing is employed*	*Echelon inventory policy is used*
Order-up-to-S policy	No bullwhip effect	Bullwhip effect significantly decreases	Further decrease in bullwhip effect
System dynamics anchor-and-adjust policy	No bullwhip effect	Bullwhip effect significantly decreases	Further decrease in bullwhip effect
(s,S) policy	No bullwhip effect	Bullwhip effect significantly decreases	Further decrease in bullwhip effect

There are several well-known business practices to implement demand information-sharing and/or Echelon-inventory policies: Collaborative Planning, Vendor Managed Inventories (VMI), Continuous Replenishment Programs (CRP), information systems like Electronic Data Interchange (EDI), Point of Sale (POS) applications, and more recent developments like Web-based Transactions, and Radio Frequency Identification (RFID) tags in lieu of bar codes (see Nahmias, 2009 and Lee *et al*, 1997 and 1998). Disney SM and Towill DR (2003) analyze the effects of VMI structures on two particular sources of the bullwhip effect (demand signal processing and order lead times). They demonstrate by simulation experiments that the bullwhip effect is reduced significantly if VMI structures are compared to the traditional serial chain structure. Disney *et al* (2004) analyze the impact of information and communication technologies (ICT) on the bullwhip and supply chain performance. They conclude that although there are benefits of ICT on bullwhip and supply chain performance, such policies should be implemented carefully because of the added complexities to the decision making process. Holweg *et al* (2005) classify supply chain collaboration initiatives based on inventory replenishment and forecasting collaboration dimensions. They claim that collaboration in inventory replenishment alone (eg VMI) or forecast sharing alone is not sufficient to achieve significant improvement in the bullwhip effect. Shared information should be used in supplier's forecasting and inventory control processes in order to gain substantial improvements in the bullwhip.

Conclusions and future work

Three typical ordering policies are considered and modelled in the context of a supply chain. Numerous simulation experiments are carried out using each of the three policies. These experiments analyze two groups of factors: policy-independent parameters of the supply chain and policy-specific parameters for each policy.

The most general conclusion of the experiments is that the bullwhip effect (amplification of orders along the supply chain) results in all cases and policies, as long as each stage utilizes local uncoordinated forecasts based on incoming orders (or demand). So, uncoordinated local demand forecasting is confirmed to be as a main cause of the bullwhip effect. An extension of this result is that the level of' 'responsiveness' of forecasts to the demand influences the magnitude of the bullwhip effect experienced. Forecasts that are highly responsive to the changes in the demand increase the bullwhip effect, while less responsive forecasts decrease it. The weight of demand forecasts in the ordering equation is another important factor that determines the bullwhip effect. If the weight of demand forecasts in ordering equations is high, then the magnitude of bullwhip is also high. If forecasts are not used in ordering equation at all, then the bullwhip effect does not exist. Thus, if the demand pattern is known (and/or it changes very slowly), the bullwhip effect may be avoided by not using the demand forecasts in ordering equations or by using very slow-response forecasts.

Two other factors were partially analyzed by simulation experiments: supply line LT and *batching* of orders. Experiments show that LT by itself is not sufficient to create the bullwhip effect. But given that there is already a bullwhip effect caused by local demand forecasting (or *order batching* or *shortage gaming*), LT does amplify the bullwhip substantially. Increased level of batching of orders and increased LT, both cause amplified bullwhip effects. Batching of orders by itself is sufficient to cause an order amplification from the retailer to the next stage, the wholesaler. But this amplification is limited, as it does not propagate to the other stages, if all agents use the same degree of batching. For the bullwhip caused by order batching to propagate through the entire chain, agents up stream must use increasing degrees of order batching.

Lastly, we tested demand and forecast information-sharing strategies against the bullwhip effect, as suggested by the literature. These strategies significantly reduce the bullwhip effect in all ordering policies. However, demand and forecast sharing cannot completely *eliminate* the bullwhip; it can *reduce* it. Bullwhip effect will exist to some extent in the supply chain as long as the ordering policies use isolated demand forecasts (or there is shortage gaming, or price variations). The information-sharing strategy implies managerial practices like Collaborative Planning and VMI. It also necessitates information systems like EDI, POS applications, Web-based Transaction Systems, and RFID tags in lieu of bar codes. To avoid excessive batching, a contributor to bullwhip, CRP can be used. To shorten the LT, another bullwhip amplifier, Quick Response (QR) systems can be implemented.

There are two other major causes of the bullwhip effect known in the literature: shortage (rationing) gaming and price variations. These two factors, necessitating more detailed and complex modelling, are beyond the scope of this study and constitute further research areas. Finally, information sharing on supply *network* structures is another potential research topic. Advanced forecasting models involving extrapolative methods and more sophisticated ordering policies and can be tested in such more realistic and complex settings.

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