Supply Chain Decision Making: Will Shorter Cycle Times and Shared Point-of-Sale Information Necessarily Help?

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Using a simulated supply chain experiment based on the well-known "beer game," we examine how changes in order and delivery cycles, availability of shared point-of-sale (POS) information, and the pattern of customer demand affect supply chain efficiency. We find that speeding up cycle time is beneficial, but the sharing of POS information is not necessarily so. Whether or not the sharing of POS information is beneficial depends on the nature of the demand pattern represented by the POS information. If the demand pattern conveys continual change in ultimate downstream customer demand (as does an S-shaped demand pattern), the POS information can distract the upstream decision maker from what is perhaps more immediately relevant information, orders placed by the proximate downstream agent and the supply line.

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Introduction
In traditional supply chains, orders move upstream and shipments flow downstream. Based on the locally available information (the flows of incoming orders from downstream members and shipments from upstream members), each member of the supply chain attempts to simultaneously minimize inventory on hand and stockouts. These dual tasks are rendered especially complex because of: (i) ordering and shipping delays between supply chain levels and (ii) the dependence of each chain member’s performance on the quality of other supply chain members’ decision making. This structure has produced alternating periods of stockouts and surpluses in many industries (e.g., personal computer memory chips, textiles), especially upstream in the chain, throughout a wide span of time (Burke 1988, Fisher et al. 1994).

These observations are closely related to the “bullwhip effect” that has been studied in the theoretical literature (cf. Lee et al. 1997b); i.e., orders to the supplier tend to have larger variance than sales to the buyer. Furthermore, this distortion propagates upstream the supply chain in an amplified form. The alternating periods of stockouts and surpluses that occur in the industries referred to earlier naturally follow. Indeed, this distortion of demand information and its concomitant higher variance (along with the consequential alternating stockouts and surpluses) lead to large cost inefficiencies. While some have characterized the bullwhip as the result of rational responses to common operations (Lee et al. 1997b), Chen (1999, p. 1083) outlined conditions under which the effect would disappear.

Two paths can lead to the bullwhip inefficiencies observed in supply chains. First, the chain design itself may be inefficient (e.g., too many levels, long delays between and/or within levels, poor transfer of information between levels, etc.; see Buzzell and Ortmeyer 1994; Lee et al. 1997a). Second, the suboptimality could result from the biases so often observed in judgment and decision making (e.g., ignoring interdependence, biased forecasting, etc.). For example, in a seminal experiment, Sterman (1989) attributes laboratory-observed supply chain inefficiencies to decision makers’ (DM’s) inabilitys to account for long
time delays between the placing of an order and its receipt.

Of course, the two paths interact. People make decisions in the context of a system’s structure. They may make mistakes that they would not if the system were somehow altered. Therefore, it is essential to consider both structure and decision making. For better or worse, however, industry improvements have focused on reengineering. Impatient with the bulbiness effect and its accompanying inefficiencies, several companies have invested (e.g., Buzzell and Ortmeyer 1994 mention Wal-Mart, P&G, GE’s Appliance Division, and Baxter) large sums of money to reengineer their supply chains (Coopers & Lybrand 1992, National Retail Federation and Andersen Consulting 1992). Two elements of this trend are speeding up the intrasystem and intersuppliers’ chains (Stalk and Hout 1990) and the sharing of point-of-sale (POS) information throughout the supply chain (Gill and Abend 1997, Lee et al. 1997a).

Recent literature presents theoretical work on the effect of some of these developments. In particular, Lee et al. (1997b), Chen (1999), Chen et al. (1999; 2000a, b) provide analyses of the impact of shortening the time lags within the supply chain. Similarly, Cachon and Fisher (2000), Chen et al. (1999; 2000a, b), Lee et al. (2000), and Raghunathan (2001) analyze issues related to POS information sharing. Not surprisingly, all suggest that shorter time lags and more information sharing are better.

However, readers of the behavioral decision theory literature are well aware that modifications of decision contexts designed to improve decisions often do not when utilized by human beings. This is particularly true when the modification provides “more” information (e.g., Kahneman and Tversky 1973). With the current and anticipated growth of technology-based systems that speed up the flow of information and goods among supply chain members (e.g., quick response, efficient consumer response, consumer replenishment programs, vendor-managed inventory, or even just electronic data interchange) or more comprehensive business practices that draw on several organizations to help bring products to market (e.g., collaborative planning, forecasting, and replenishment—CPFR1), we believe it is crucial to begin a systematic research effort aimed at understanding the efficacy of reengineering the traditional supply chain under various environmental scenarios, the critical role of human judgment and decision making, and the interaction between these factors.

Therefore, our objectives in this paper are to address the following specific issues:

(i) To what extent do structural changes that speed up the order and delivery cycles (by reducing the order processing, storing, and shipping lags) impact cost efficiency?

(ii) To what extent does timely sharing of information between supply chain members (by transmitting the retailer’s POS information to all other supply chain members) impact cost efficiency?

(iii) What is the impact of the nature and extent of uncertainty in customer demand (as represented by the shape and volatility of incoming customer demand) on the results obtained in (i) and (ii) above?

We conducted a simulated supply chain experiment to answer these questions. It is important to note that the paper is not about supply chains in vivo. It is about the decision-making processes that are inherent to supply chain management. As such, the external validity of our results will be subject to question.

We examine two lead-time conditions in this paper: one with two-period ordering and shipping delays (i.e., at least a four-period interval between order placement and receipt) between each successive stage in the chain as in Sterman (1989), and a shorter single-period delay (i.e., at least a two-period interval). We also examine two POS conditions: one where the customer demand is known to the retailer only, and another where the POS information is made immediately available to every supply chain member.

We found that reducing the cycle time through shorter lags, predictably, reduced the inventory and stockout costs. However, the effect of POS information availability was contingent on the nature of the customer demand being served by the supply chain. Whereas POS availability led to the expected improvements in the simplest demand environment, efficiency was not helped, and was even impaired for some supply chain members under more dynamic patterns of customer demand!

Finally, Sterman showed that a single change in a constant level of customer demand continued to cause order and inventory fluctuations that never disappeared! However, for most subjects, one-time-only changes and uniformly distributed demands would be very unusual. In fact, Sterman (1989, p. 336) himself wondered whether “behavior (would) differ if customer demand followed a more realistic pattern.” Consequently, we investigate the effects of the supply chain modifications under three separate demand environments: a step-up demand function similar to Sterman’s, an errorless S-shaped pattern, and an S-shaped pattern with stationary disturbances.

The well-known “beer game” provides a natural choice for our simulating decision making in a supply chain under a wide range of conditions. See Sterman (1989, 1992) and Croson and Donohue (2002) for background and details on the beer game.

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1 See http://www.cpfr.org.
Experiment

Design

The experimental design is a 2 (order and shipping LAGs of one or two periods) × 2 (POS information is available to all supply chain members—y, or only to the retailer—n) × 3 (customer DEMAND patterns: step-up—SU, S-shaped without error—SN, and S-shaped with error—SE) full factorial. In all, usable data were collected for 300 subjects in 100 supply chains. Individual cell sizes are shown below (due to scheduling conflicts and a few computer errors, the cell sizes are unequal).

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The simulation was run using network-connected personal computers. For the POS = y condition, where every supply chain member can see the retail-level demand, pressing the F5 key brought up a screen showing those sales up to the current period. Those in the POS = n condition simply did not have access to the F5 key. Shipping and ordering delays were changed by transmitting the orders (shipments) to the upstream (downstream) member two periods (LAG = 2) or one period (LAG = 1) after their initiations. Finally, the input consumer demand patterns were readily changed by choosing one of the three demand patterns.

Procedures

Two days before their assigned simulation, participants (day and evening students in an MBA program) were given a basic description of the game and provided with reading material to familiarize themselves with the computerized setup. Upon arrival on the scheduled date, supply chain roles were assigned and additional role-specific information was provided. All orders and shipments flowed within a three-person supply chain. Each participant sat at a separate terminal.

The simulation began with an eight-period trial phase. Each trial period lasted two minutes, with additional stoppages for answering questions. After the trial phase, participants began what they believed was the actual 48-period simulation (we stopped after Period 36 to minimize end-game effects). Costs incurred during this 36-period phase (stockout costs: $1 per thousand cases, holding costs: $0.50 per thousand cases) were used to determine final payoffs.

To make their decisions, participants had 90 seconds during the first six periods, and 70 seconds subsequently. Extensive pretesting had shown these lengths to provide a reasonable balance between rushing the decisions and having too much time. A timer displayed the elapsed time on the screen, and the input box flashed during the last 15 seconds in the event that no decision had been entered. The pipeline was initialized with inventory on hand of 50,000 cases and incoming shipments of 30,000 cases. These initial values ensured that supply chain members had neither too much nor too little inventory on hand during the initial periods. After the end of the simulation, participants’ payments were determined according to the total costs incurred by their entire supply chain. Possible payoffs ranged from $5 to $25. The average was $15.

In the event that one or both of our experimental manipulations (LAG reduction and POS availability) do indeed enable subjects to be more efficient within the system, benchmarks become necessary to assess the actual degree of improvement. In other words, if we want to gauge precisely how effective the manipulations are in improving human performance, we need to know what the limits of that performance are.

"Optimality" Benchmarks

Chen (1999) calculates "optimal" behavior in a supply chain where the members of the chain share the common goal of optimizing the chain’s performance as a whole (i.e., they act as a team) and retailer demand follows a stationary, known stochastic process. In contrast, our demand processes are both non-stationary and unknown. These differences, especially the unknown nature of the demand process, make it impossible for a decision maker to calculate an optimal strategy a priori. Therefore, they are likely to invoke simple heuristics and rules (Tversky and Kahneman 1974). We follow Sterman in offering a benchmark based on an anchoring and adjustment decision rule that subjects are assumed to have used. Our benchmarks are based on subjects using "optimal" forms of this decision rule. It is in that sense, not the sense of what specific decisions would globally minimize costs, that our benchmarks reflect the limits of human performance.

Sterman implemented the following mental model form:

\[ DO_t = F_t + \alpha_t (I^*_t - I_t) + \alpha_{SL} \left( \lambda F_t - \sum_{i=1}^{\lambda} O_{t-i} \right) \]

where \( DO_t \) is the desired order at time \( t \); \( F_t \) is the forecast of downstream member’s incoming order for period \( t \) (a function perhaps of the historical ordering pattern of the downstream customer); \( I_t \) is the inventory on hand in period \( t \); \( I^*_t \) is the desired inventory.

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2 The usual implementation of the beer game uses four levels: retailer, wholesaler, distributor, and factory. Two intermediate decision makers are included. We eliminated one and assigned the distributor the most upstream position. The wholesaler then became the only intermediate decision maker.
mark costs were obtained by optimizing the system of
decision rules (2) in the beer game, one rule
equation for each role, with respect to \( \alpha_{sl}, \alpha_{i}, \) and \( I^* \). The
optimization was performed assuming each member of
the supply chain used a rule of the form (2) to
generate orders. Product flow was simulated from
these orders. Total supply chain cost was calculated
from the simulated inventory and stockouts. The cost
was then minimized with respect to the nine param-"
of the notion that behavior is suboptimal. Nevertheless, subjects seemed much better able to deal with the S-shaped response function than the step-up one. The step-up demand pattern is extremely disruptive.

Table 1 indicates whether the LAG manipulation produces significant differences between the LAG = 1 and LAG = 2 conditions. For example, for the S with error condition the cost difference due to LAG for the retailer (1.32 – 0.97) is significantly different from zero at the 0.10 level. However, for the distributor, the analogous difference (3.11 – 3.53) is not significant (see Figure 2 and Table 1).

The benefits of reducing the ordering and shipping delays are clear for the step-up and S-no error demand patterns. Once error is introduced, however, the benefits are not as clear, especially for the distributor. The supply chain still shows improved performance, but because the distributor actually does worse (though not significantly) for the shorter lag, the improvement is not significant. The important conclusion is that faster cycle times do help, but the magnitude of improvement is moderated by the underlying demand pattern. The differences are clearest for the simpler demand patterns (step-up and S-no error). The differences (both absolute and proportional) are also greater in magnitude for the step-up demand pattern. This is not surprising because the step-up demand pattern produces the most inefficient behavior to begin with, and consequently the LAG = 2 case has more room for improvement.

Next, we consider the propagation of inefficiency as we go upstream. The bullwhip effect would imply significant positive differences in total costs between pairs of upstream-downstream supply chain members. Table 2 shows whether the differences are significant (1-sided test, p < 0.10).

For step-up demand, the bullwhip effects are clear in both LAG conditions. However, this result does not hold up for either one of the S-shaped patterns. The relatively high costs of the wholesaler actually cause the difference to be negative for the distributor-wholesaler pair. One possible explanation for the result is that it is caused by how the system deals with decision-making inefficiencies in the face of the particular demand pattern. In particular, the nature of the S-shape is that it is increasing, and consequently does not push the supply chain into excess inventories to the same degree.

Combined with the benchmarks, these results imply that the bullwhip effect is not inevitable. This phenomenon may well be contingent on the complexity of the customer demand pattern (which is generally not under managerial control) and on the predictability of downstream and upstream DM’s actions (which may well be responsive to managerial actions). However, even in the step-up case, the
Figure 3 Costs (in Thousands) by POS and Demand Conditions

(a) Step-up Demand

(b) S-Shaped Demand Without Error

(c) S-Shaped Demand with Error

The benefits of providing POS information are again clearest for the step-up demand function. It is the only demand pattern for which there is any improvement in total supply chain costs! By contrast, the two S-shaped demand patterns actually result in worse performance with POS information. Examining the means in Figure 3, it is clear that whereas the retailer and the wholesaler do not benefit greatly, the distributor actually does worse with POS information available. One possible explanation is that the salience of the POS information is distracting the distributor from other information, such as wholesaler orders, that is more relevant to the task at hand (Glazer et al. 1992). By reacting independently to customer demand, performance actually worsens! This problem is not as serious for the wholesaler, perhaps, because greater proximity to the final customer makes the salient POS information more relevant.

The pattern of costs examined thus far shows that the basic results reported by Sterman do in fact persist for the step-up pattern even when the cycle time is shortened and supply chain members have shared POS information. However, the result pattern does not fully survive under S-shaped customer demand patterns. Perhaps most surprisingly, we find that the availability of POS information can sometimes even impair the entire supply chain's performance.

### Discussion

#### Summary

In this paper we have examined decision making in a dynamic and interdependent task environment. While such environments typify the operations of many supply chains, decision-oriented research is generally lacking. Building upon Sterman’s landmark work, we examined the beer game under a wider range of circumstances. Specifically, we examined how supply chain efficiency is affected by changes in the time it takes to transmit orders and shipments (LAG), the availability of POS information, and the pattern of changes in customer DEMAND.

We found that reducing the cycle time (LAG) results in the greatest benefits in cost reduction across all experimental conditions, although the extent of improvement is somewhat mitigated by the pattern of change in customer demand.

Surprisingly however, we found that sharing POS information is unambiguously beneficial only in Sterman’s step-up demand pattern. When the demand pattern was S-shaped (with or without error), POS sharing actually hurt performance. This is in stark contrast to theoretical literature that suggests the reverse (Chen et al. 1999, 2000a; Lee et al. 2000; Raghunathan 2001).

The step-up demand pattern is quite unique. It has only a single change in demand. Subjects were less capable of dealing with it than they were of more
continuous changes in demand. Fortunately, the real world presents demand patterns that tend to be less disruptive than the step-up one.

S-shaped demand brings a consistent pattern of change. In the $\text{POS} = y$ condition, subjects had the opportunity to observe that change. As such, POS sharing presented a salient piece of information for the subjects. Its relevance to supply chain goals is obvious; it is the demand the chain ultimately has to fill. It is very tempting for subjects to give this information large weight in their decisions. However, cost minimization requires that each supply chain member carefully balance orders from immediately downstream agents and the supply line. The salience of the information in $\text{POS} = y$ induces a disruption. Subjects therefore gave POS information more weight than perhaps they should have (Glazer et al. 1992).

In contrast to the S-shaped demand functions, POS information sharing in the step-up demand presents no such salient information. With the exception of the single disruption, there is really no information in the $\text{POS} = y$ condition. Nothing changes, so there is no disruption imposed on the DM’s capabilities.

In sum, with the great changes currently underway in relations between vendors and their supply chain customers, it is incumbent upon the research community to begin a concerted effort to understand how the new relations can be managed most efficiently. One approach for such research is a systematic laboratory exploration of the issues identified here.

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