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DYNAMIC DECISION MAKING IN MARKETING CHANNELS

An Experimental Study of Cycle Time, Shared Information and Customer Demand Patterns

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ABSTRACT

Using a simulated channel experiment, we examine how changes in order and delivery cycles, availability of shared Point-of-Sale information, and the pattern of customer demand affect channel efficiency and the characteristics of decision making by channel members. We find that speeding up cycle time is beneficial, but sharing POS information is not necessarily so! Further, we identify three sources of systematic decision making inefficiencies in dynamic and interdependent tasks: *complexity, overreaction,* and *inadequate coordination.*

INTRODUCTION

Consider the distribution channel shown in Figure 1.

Insert Figure 1 about here

In traditional channels, orders flow upstream and shipments move downstream. Based on the locally available information (the flows of incoming orders from downstream members and shipments from upstream members), each channel member attempts to simultaneously minimize inventory-on-hand and stockouts. These dual tasks are rendered especially complex because of: *i)* ordering and shipping delays between channel members; *ii)* uncertainties regarding customer demand and the external environment; and *iii)* the dependence of each channel member's performance on the quality of other channel members' decision making (e.g., poor decision making by the wholesaler can adversely impact the in-stock position of a retailer, even if the retailer is perfectly prescient about the incoming orders from customers). The resulting set of dynamic and interdependent decisions have often been found to result in large inefficiencies for the channel as a whole. For example, Hammond (1992) reports that the 100 billion dollar apparel industry incurs a penalty of as much as 25 billion dollars for being out of stock at some times, and having to offer markdowns because of excess inventory at others. Similar alternating periods of stockouts and surpluses have plagued many industries (e.g., personal computer memory chips, textiles, shoe leather) throughout a wide span of time (Burke 1988; Fisher, Hammond, Obermeyer and Raman 1994; Mack 1956).

Impatient with the inefficiencies so typical of many traditional channels, several companies have invested (e.g., Buzzell and Ortmeyer, 1994, mention Wal-Mart, P&G, GE's Appliance Division and Baxter), or are considering investing (Coopers & Lybrand 1992, National Retail Federation and Andersen Consulting 1992), large sums of money to re-engineer their distribution processes. The hope is that greater decision making efficiency will result in substantial economies. Recently, Kurt Salmon and Associates (1993) estimated that re-engineered processes and more efficient decision making could save the grocery industry as much as thirty billion dollars in inventory costs.

Yet, academic research on decision making in such dynamic and interdependent task environment is rare. Whereas the marketing channels literature provides many studies regarding the nature of relationships between channel members (see, e.g., Dwyer, Schurr and Oh 1987, and Frazier, Spekman and O'Neal 1988), and the impact of a channel members' strategy on the strategic behavior of other channel members (see, e.g., McGuire and Staelin 1983 and Moorthy 1988), studies of day-to-day operating decisions, the resulting need for coordinated actions, and the impact of various channel flows on efficiency are absent. In the decision making literature, save Sterman (1989a and b) and Glazer, Steckel and Winer (1992), most studies either deal with static situations, or fail to account for interdependence among multiple decision makers (Brehmer 1992). With the current and anticipated growth of technology based systems which speed up the flows of information and goods among channel members (e.g., Quick Response, Efficient Consumer Response, or even just Electronic Data Interchange) we believe it is crucial to begin the systematic study of managerial decision making under a wide variety of channel and external conditions.

Using a simulated channel experiment (based on the well known "Beer Game", see Senge 1990, Sterman 1989a) our objectives in this paper are to address the following specific issues:

i) to what extent do structural changes which speed up the order and delivery cycles (by reducing the manufacturing, storing and shipping lags) impact decision making efficiency and the decision calculus employed by each channel member?

ii) to what extent does timely sharing of information between channel members (by transmitting the retailer's Point-of Sale (POS) information to all other channel members) impact decision making efficiency and the decision calculus employed by each channel member?

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 found that reducing the cycle time through shorter lags, predictably, reduces the inventory and stockout costs. But, the effect of POS information availability was contingent on the nature of the customer demand being served by the channel. Whereas, POS availability led to the expected improvements in the simplest demand environment, efficiency was not helped and was even impaired for some channel members under more realistic (and less predictable) patterns of customer demand! Further, by examining the decision maker's (DM's) mental calculus under a variety of experimental conditions we surmise that in addition to paying insufficient attention to the supply line (as posited by Sterman 1989a), the quality of decision making suffers due to: the *complexity* of the decision; *inadequate coordination* among DMs; and *overreaction* to small or irrelevant changes in demand.

BACKGROUND

Our study builds on Sterman's (1989 a) experiment of interdependent decision making in a dynamic, but, traditional distribution system. In his experiment, Sterman found that a single one-time change in customer demand resulted in long term inefficiencies within a distribution channel. Specifically, orders and inventory were characterized by large fluctuations (*oscillations*), increasing amplitude and variance the further away the DM was from the end consumer (*amplification*), and later peaks in order rates as one moved further up the channel (*phase lag*).

Two classes of possible causes emerge for these results. First, the channel design itself may be inefficient (e.g., too many levels, long delays between and/or within levels, poor transfer of information between levels, etc.) rendering decision making much too complex. Several authors (e.g., Martin 1993, Stalk and Hout 1990) have suggested that efforts be concentrated on *speeding up the intra- and inter- channel flows and simplifying the system.* Several companies have benefited from following this approach (see, Buzzell and Ortmeyer 1994, and Davidow and Malone 1992). Second, the sub-optimality could result from the limitations and biases so often observed in judgment and decision making (e.g., ignoring interdependence, biased forecasting, inadequate updating of the DM's mental model of the task at hand, etc.). In particular Sterman (1989a, p. 334) concluded that:

> To understand the source of the oscillations it is necessary to consider how the subjects dealt with long time lags between placing and receiving orders -- the supply line. The results show that ***most subjects failed to account adequately for the supply line*** (emphasis added).... Thus it appears that subjects failed to allow for sufficient (product) in the pipeline to achieve their desired inventory level.

In agreement with Sterman's conclusion, Senge (1990) and Kleinmuntz (1990) suggest that efforts should also be focused on improving the *quality* of the decision making activity. Kleinmuntz, in particular, suggests that the biases and inefficiencies noted in Sterman's paper should be more closely examined under a variety of circumstances, where the DM is better and more easily informed about customer demand and the state of the pipeline. And Senge suggests that a systematic analysis of the cognitive biases in DMs' mental models provides a promising direction for improving the quality of dynamic decisions made in the context of an interdependent system.

Clearly, both approaches (re-engineering and improved understanding of the decision environment) have merit. In fact, Kurt Salmon and Associates' (1993) report for the Food Marketing Institute emphasizes that companies who want to make significant improvement will have to do both. A systematic research effort aimed at understanding the efficacy of re-engineering the traditional channel under various environmental scenarios, the critical role of judgmental decision making (Kleinmuntz 1990, Towill 1992), and the interaction between these factors should therefore prove fruitful.

The complexities characteristic of an interdependent multi-level system render the calculation of optimal behavior virtually impossible for the individual channel member (Sterman 1989a). Thus, we assume that DMs resort to simplifying heuristics (Cyert and March 1963; Simon 1982). The mental calculus of each DM is therefore represented with the anchoring and adjustment heuristic (Tversky and Kahnemann 1974) adopted by Sterman (1989a), and routinely used to model industry level sales and inventory data in the production smoothing literature (see e.g., Bechter and Stanley 1992, and Blinder and Maccini 1990). Specifically, each DM's calculus for any given period is represented thus:

(1)	**DESIRED ORDER**	=	**Expected Incoming Orders**	+ **Adjustment for Desired Inventory Level**	+	**Adjustment for Desired Supply Line**
	where each term is based on		• DM's forecast of future incoming orders	• Desired safety stock • Current inventory/backlog		• Total delay in receiving shipments against orders • Average sales / period • Pending shipments

Note that (1) implies that past decisions and outcomes will influence current and future decisions (dynamics), and the required adjustments depend crucially upon others' performance (interdependence). We shall use (1) to model the subjects' decision calculus and gain insights about the reasons for variations in channel and individual performance.

The Value of Re-Engineering, or, Shortening Order and Delivery Lags

Longer lead times should make the channel less efficient for several reasons. First, because orders placed and shipments sent a long time ago might still be in the pipeline, the DM must make appropriate adjustments for pipeline delays (the third term in (1), the DM's calculus). Past research shows that paying attention to complex relationships among events and decisions in the past is difficult (Hambrick 1982; Sterman 1989a and b). Second, longer delays in feedback impede learning (Hogarth 1987), compounding the first problem. In a single-DM task Brehmer (1992) found that even minimal delays effectively prevented the DM from making any significant adjustments at all. Finally, longer lead time makes the forecasting task (the first term in (1)) less accurate because predictions must be made for a period farther out into the future. Greater demand uncertainty calls for an increase in the desired inventory (the second term in (1)) and results in higher costs (Fisher et. al. 1994).

We examine two conditions: one with two period ordering and shipping delays between each successive stage in the channel, and a faster single period delay.

The Value of Shared POS Information

Each channel member incurs carrying and stockout costs based on the ability to fill orders received from the channel member immediately downstream (*e.g.*, the distributor is most immediately concerned about filling the orders received from the wholesaler). Consequently, accurate knowledge of *final* customer demand is of obvious importance to the retailer. But, it is important to recognize that *ultimately* the entire channel is also attempting to fill this *same* customer demand. So, if the only information about customer demand transferred to upstream members is in the form of orders from downstream members, the attendant distortion could mislead the upstream members in their inventory and ordering decisions for two important reasons. First, there is an obvious problem due to the delays created by ordering lead times. Second, the upstream member is forced to guess how much of the change from the downstream member's "normal" order level is due to future expectations of customer demand, and how much of the change reflects adjustments to the downstream member's safety stock (the first and second terms of (1) are completely confounded). Because it is natural to expect the incoming orders to be noisy themselves, such mismatching can cause the variance of orders to increase as one moves upstream (the amplification phenomenon) (Lee, Padmanabhan and Whang 1994). Providing customer demand information to each channel member, however, could mitigate this consequence by allowing channel members to "coordinate" their decisions without explicit communications. Thus, shared POS information can be expected to reduce the uncertainty faced by each DM and increase efficiency (Towill 1992).

A potential drawback of providing the extra information is that it could overload the DM's cognitive abilities (Kleinmuntz 1990), resulting in poor performance. As Glazer, Steckel and Winer (1992) have shown, salient information can have a distracting, deleterious effect on managerial performance, ***even if the DMs know how to use it!*** This happens because managerial attention is drawn away from other relevant (but less salient) pieces of information. The extent to which the benefits from implicit "coordination" and reduced uncertainty will be countered by cognitive overload and distraction deserves careful examination. We examine two conditions: one where the customer demand is known to the retailer only, and another where the POS information is made immediately available to every channel member.

Patterns of Customer Demand

Clearly, meeting customer demand efficiently is easiest when it is stable or constant. The more meaningful issue is how well DMs adjust to changes? In Sterman's study, a one-time change in customer demand in period 5 continued to cause order and inventory fluctuations until period 36! But, for most subjects, a one-time change in demand is very unusual (the priors on encountering such a pattern would be extremely small). In fact, Sterman (1989a, p. 336) himself wondered whether "subjects' behavior (would) differ if customer demand followed a more realistic pattern."

How well can we expect DMs to perform when customer demand changes according to a more realistic and expected pattern? To a population of business school students, the S-shaped curve is probably much more realistic and expected. But, while a more familiar pattern should be expected to help improve performance, Wagenaar and Timmers (1979) found that subjects display a "non-linear extrapolation" bias, systematically under-forecasting an (exponentially) increasing process. For S-shaped demand, this should lead to shortfalls and stockouts during the growth phase. The precise manner in which such a consistent tendency towards more frequent stockouts can be expected to impact stability and amplification upstream deserves careful examination.

Finally, while it is clear that overall efficiency will decrease as random volatility in customer demand increases, the impact of such a pattern on upstream variance and amplification deserves further study. Consequently, we investigate the effects of the channel modifications (shorter delays, shared information) 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 added error. See Figure 2.

Insert Figure 2 about here

The "Beer Game" developed and used over the years at MIT (Forrester 1958, Sterman 1992, 1989a) for teaching and research is a natural choice for simulating decision making in an interdependent channel under a wide range of conditions. We describe it next.

The "Beer Game"

Insert Figure 3 about here

In the basic "Beer Game" setup, depicted in Figure 3, the retailer receives customers' orders and places orders with the wholesaler.[1] In turn, the wholesaler places orders with the distributor, and the distributor with the factory. At each stage, there is a two period delay in order transmission. Upon receipt of orders, each DM ships as much as current inventory allows, and backlogs the rest for future delivery (with the exceptions that unfilled orders at retail are lost forever and the factory is always able to ship the ordered amount after the two period delay). It takes two additional periods for the shipments to reach the next downstream entity. Thus, it takes *at least* four periods for a retailer to receive shipments against a particular order. However, if the wholesaler does not have sufficient inventory, the delay can be much longer (an out-of-stock wholesaler would have to wait additional periods for shipments to arrive from the distributor, who also may be out of stock!). Finally, each DM has access only to local information (own past orders, current and past incoming orders, inventory and incoming shipments). So, neither the wholesaler nor the distributor observes actual customer demand at the retail level. Nor is anyone aware of the current inventory and order position of other channel partners.

Players of the "Beer Game" are instructed to minimize their costs during the game. Costs are composed of two elements, inventory holding costs and stockout costs (cost for each unfilled order) with stockout cost per unit being twice holding cost per unit. Costs are assessed at each level of the channel. The game consists of a series of decisions. It begins with each channel member having an initial inventory. The first step in each decision period involves the receipt of incoming

[1] Figure 3 presents a shortened version of the "Beer Game". The original setup contains one more middleman. We eliminated this intermediary in order to economize on subjects (each channel would require three instead of four, or an extra 100 subjects) for our experiment.

inventory which is added to the current stock. Of course, this inventory was ordered at least four periods ago (more in the case of upstream stockouts). At the beginning of the game, the pipeline is well stocked in the sense that each player is told that they have ordered a specified number of units over the last four periods. This is done to ensure that no order backlogs will exist until at least the first orders placed by the players are received. The next step involves the filling of orders to the extent possible. The amount of inventory it takes to fill an order is the sum of incoming orders and any backlog (unfilled orders from previous periods) carried from the prior period. These must be satisfied whenever encountered by the wholesaler and distributor. The final step in each period, ***and the only step that involves a decision,*** is the placement of orders for the next period.

In the typical application of the "Beer Game", end-customer demand follows a simple Step-up function. It begins at a constant level, stays there for four periods, and then doubles in period five. It remains at this level for the remainder of the game. The game lasts 36 periods. For additional detail the reader is referred to Senge (1990), and Sterman (1992, 1989a).

EXPERIMENTAL PROCEDURES

Experimental Design

The experimental design is a 2 (order and shipping LAGs of 1 or 2 periods) X 2 (POS information is available to all channel members, *y*, or only to the retailer, *n*) X 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 100 channels. Individual cell sizes are shown below (due to scheduling conflicts and a few computer errors, the cell sizes are unequal).

Lag	1	1	1	1	1	1	2	2	2	2	2	2
POS	N	N	N	Y	Y	Y	N	N	N	Y	Y	Y
Demand	SU	SN	SE	SU	SN	SE	SU	SN	SE	SU	SN	SE
Number	9	7	8	10	5	9	11	5	9	13	6	8

The simulation was run using personal computers connected through a Novell network (copies of the program are available from the authors for a fee). Among other things, the computerized version permitted providing the subjects with historical data and information about incoming shipments (by pressing specific function keys), helped the subjects with the basic accounting arithmetic, and afforded greater control over intra-channel communications than is usually possible in the standard board game implementation of the simulation. Note that the history and information screens also provided additional feedback to the DMs, as recommended by Kleinmuntz (1990).

Computerization also considerably eased the task of operationalizing the treatments. For the *POS=y* condition, where every channel member can see the retail level demand, simply 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 its initiation. Finally, the input consumer demand patterns were readily changed by choosing one of three historical patterns (see Figure 2) available to the program.

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 reading material to familiarize themselves with the computerized setup. Upon arrival on the scheduled date, channel roles were assigned and additional role-specific information provided. Each participant sat at a separate computer terminal. The retailers were all seated in one bank, then the distributors in another, and finally the wholesalers. Participants were unaware of who their other channel partners were (all orders and shipments flow *within* a 3-person channel. There was no interaction *across* the several channels that were being run simultaneously).

The simulation began with an eight period trial phase (each period lasting 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 in period 36 to minimize end-game effects). Costs incurred during this 36 period phase (stockout costs: $1 per case, holding costs: $0.50 per case) were used to determine each participants' final payoff. To make their decisions, participants had 90 seconds during the first six periods, and 70 seconds subsequently. Extensive pre-testing 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 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 channel members had neither too much nor too little inventory on hand during the initial periods.

Each period, the computer screen displayed the incoming and on-hand amounts for orders and shipments, and provided the subjects an opportunity to examine historical data. The cumulative stockout, inventory holding and total costs incurred by each member were also displayed. After the end of the simulation, participants' payments were determined according to the total costs incurred by their entire channel. So, their motivation was to make the best decisions for the entire channel, not just for themselves. Possible payoffs ranged from five to twenty-five dollars. The average was fifteen.

ANALYSIS AND RESULTS

The Impact of LAG on Costs

Figure 4 shows the total costs (stockout plus inventory carrying) for each channel member and the entire channel, for each LAG within each Demand condition. Table 1 indicates whether the LAG effect is significant or not. For example, for the S with Error condition the cost difference due to LAG for the retailer (1.320-0.969) is significantly different from zero at the .10 level. However, for the distributor, the analogous difference (3.111 - 3.529) is not significant (see Figure 4 and Table 1).

Insert Figure 4 and Table 1 about here

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 channel still does show 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).

Next, consider the propagation of inefficiency as we go up the channel (amplification). Amplification would require significant positive differences in total costs between pairs of upstream-downstream channels members. Table 2 shows whether the differences are significant (one-sided test, p-value < .10) or not.

Insert Table 2 about here

For Step-up, as in Sterman, the effects of amplification on cost 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! Why does this happen? We believe that one explanation may lie in the relative complexity of the task faced by the DM. The wholesaler faces irregularities in retailer orders (composed of the actual changes in customer orders and the retailer's added noise), and variations in lead times for distributor shipments. Neither of the other DMs must contend with both (the retailer sees the actual demand, and the distributor is guaranteed shipment in 2 or 4 periods). The complexity faced by the wholesaler is magnified in the S-shaped conditions because these patterns may be more difficult to "learn". Finally, the penalty incurred by the wholesaler in these conditions is smaller for the easier LAG=1 condition.

Together, these results imply that the propagation of inefficiency due to the quality of decisions made by channel members 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 also on the predictability of downstream and upstream channel members' actions (which may well be responsive to managerial actions).

Impact of POS Information Availability on Costs

Figure 5 shows the total costs (stockout plus inventory carrying) for each channel member and the entire channel, for each POS condition within each Demand condition. Table 3 indicates whether the POS effect is significant or not.

Insert Figure 5 and Table 3 about here

The benefits of providing POS information are clearest for the Step-up demand function. *It is the only demand pattern for which there is any improvement in total channel costs*! By contrast, the two S-shaped demand patterns actually result in *worse* performance with POS information. Examining the means in Figure 5 it is clear that whereas the retailer and the wholesaler do not benefit greatly, the distributor actually does *worse* with the POS information available. A 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 her task (Glazer, Steckel and Winer 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 too (we shall return to the issue of independent versus coordinated actions later). Indeed, the information is that which directly impacts the decisions of the agent immediately downstream from the wholesaler. Thus, paying more attention to customer demand, rather than the orders coming in from the retailer, should prove less harmful to the wholesaler than to the more distant distributor. Empirically, too, we do not see the wholesaler's costs increase with availability of POS information.

Regarding amplification, we find additional evidence supporting the earlier conjecture regarding the wholesaler's difficult position in complex conditions. For S-shaped demand patterns the wholesaler's costs are greater than the distributor's in the most complex environment (*POS=n*) (see Figure 5, and Table 4 for significance results). However, when the dependence of the wholesaler on the vagaries of retailer's orders is reduced, (in the "simpler" *POS=y* condition), the distributor-wholesaler cost difference returns to the expected positive sign.

Insert Table 4 about here

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 channel 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 distributor's and consequently the entire channel's performance. Among the reasons for the observed results, we find some evidence in support of the hypothesis that the wholesaler, most vulnerable to decision biases of other members, performs most poorly under the most complex conditions (S-shaped demand, 2 period lags, and no POS information). Further, we find indications that, overly influenced by the POS information, the distributor maybe making inappropriate independent adjustments detrimental to her own and the entire channel's performance.

Subjects' Decision Calculus and Attention to the Pipeline

As quoted earlier, Sterman found that an important reason for the observed inefficiencies lay in the participants' tendency to pay insufficient attention to the pipeline. To reach this conclusion Sterman operationalized the basic decision calculus form (1), as follows:

$$DO_t = F_t + \alpha_I(I^* - I_t) + \alpha_{SL}(\lambda F_t - \sum_{i=1}^{\lambda} O_{t-i}) \qquad (2)$$

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^* is the desired inventory level; λ is the length of the supply line; α_I is an inventory adjustment parameter; and α_{SL} is the supply line adjustment parameter. The actual order placed in any given period is O_t = Max (0, DO_t).

Following Kleinmuntz (1990), however, we make a slight change in the formulation by making the current period's desired order a function of the previous period alone, as follows:

$$DO_t = L_{t-1} + \alpha_I(I^* - I_t) + \alpha_{SL}(L_{t-1} - O_{t-1}) \qquad (3)$$

where the forecast, F_t, is set equal to L_{t-1}, the order received from the downstream customer in the previous period, and only last period's outgoing orders, O_{t-1} are accounted for in the supply line. We choose this formulation because: *i)* it considerably simplifies the estimation process; *ii)* as Kleinmuntz has shown, in many instances this form and Sterman's more complete form result in very similar ordering patterns; *iii)* given Sterman's results, we already know that participants do not pay attention to far-in-time events and dropping them from the estimation equation is unlikely to cause any meaningful biases; and *iv)* results in the production smoothing literature (see, e.g., Blinder 1986 and Bechter and Stanley 1992) show that more sophisticated models add little.

Equation (3) can be estimated by nonlinear regression. However, for the S-shaped patterns an important caveat applies. For these patterns it is likely that as end-customer demand increases, channel members would desire to maintain larger safety stocks, I^*. Strictly speaking, then, I^* is time variant. Specifying the estimation equation as such would render the econometrics extremely difficult and unreliable. Thus, we estimate it as a single value. Such an estimated value will likely represent an average value of the parameter over the 36 periods. Therefore, magnitude comparisons across experimental conditions are still meaningful.

Overall, the decision calculus model fit the subjects' orders quite well. The following table summarizes the average ratio of explained to total variance for each role under each LAG condition (these values do not vary appreciable for the three separate demand conditions, nor does POS have a significant effect on this pattern):

	Retailer	Wholesaler	Distributor
LAG=1	0.91	0.77	0.68
LAG=2	0.86	0.78	0.61

In his analysis, Sterman relied on the size of the supply line coefficient α_{SL} to judge how much attention the subjects were paying to the supply line. Our average estimates for α_{SL} for both LAG conditions for each channel role under each demand condition are summarized in Table 5.

Insert Table 5 about here

Note first that, as in Sterman's study, the estimates of α_{SL} are close to zero. Clearly, the subjects are unable to fully account for the supply line. Nonetheless, the estimates for LAG=1 condition tend to be larger than for LAG=2 (and sometimes significantly so). Further, even though they are small, distributors do consistently have the largest supply line coefficients. Together these results suggest that while participants do underweight the supply line, they tend to correct for this somewhat when the supply line itself gets less complex. Clearly, accounting for the supply line is easier when the time transpired between placing an order and receiving the corresponding shipment is shorter (in the LAG=1 condition). Also, recall that the distributor's supply line is perfectly predictable and the distributor can see the clear relation between outgoing orders and incoming shipments quite easily. By contrast, depending on the prevailing stock position of upstream members, the total time taken to receive shipments can vary greatly for retailers and wholesalers. Consequently, the supply line is much less predictable and therefore less emphasized in decision making.

Further insights into the subjects' ability to adjust for delays and lags in the supply line can be gleaned by examining the impact of LAG and channel role on the estimated desired inventory levels, I^* (see Table 6).

Insert Table 6 about here

First, note that in general the desired inventory levels are smaller (even though not always significantly so) for LAG=1. When delays are shorter the need to keep large inventories should decrease. Thus, while the participants do not fully account for the supply line, they do make reasonable adjustments to their desired inventory levels. Second, it is interesting to note the consistent increase in desired inventory levels as we travel upstream. Clearly, each DM is making separate and, therefore, redundant adjustments to deal with demand uncertainties. As Lee et. al. (1994) have shown, such uncoordinated behavior is sufficient to cause large inefficiencies which get amplified up the channel.

In summary, across a wider range of conditions, our analysis of the DM's calculus finds support for Sterman's earlier results. However, closer examination of a variety of these conditions also suggests that inadequate attention to the supply line may not be an inherent bias but may result due to the *complexity* of fully accounting for the supply line. When the task is made simpler, the supply line coefficients do increase. Further, participants clearly show the ability to react appropriately to changes in supply line length by adjusting the desired inventory levels. Finally, due perhaps to the lack of explicit communication among channel members, we find that the desired inventory levels increase redundantly up the supply chain. Consequently, re-engineering the supply chain and better coordination should together prove most useful for improving channel efficiency.

Impact of POS on Decision Making

It is intriguing to find that channel members' costs are higher for S-shaped patterns when every channel member has access to POS information. The ability to implicitly coordinate was expected to help improve efficiency. However, the pattern of results examined so far seems to show that the distracting effect of such salient information, and independent redundant adjustments may have ended up hurting more. We examine the nature of decision making under the two POS conditions further to gain some insights into these results.

First, consider the impact of POS information on the order size. Table 7 shows the average order sizes for each channel role for each demand pattern and the associated significance comparisons.

Insert Table 7 about here

Note that for the Step-up pattern, order sizes decrease under *POS=y*. This is reasonable because for the typical channel, orders increase too much following the one time change in demand. When the customer demand pattern can be seen, participants make adjustments in the appropriate direction. On the other hand, the average order size *increases* for the S-shaped pattern. Directionally, this too is reasonable because without being able to see the actual demand, the tendency is to underestimate the growth in customer demand (Wagenaar and Timmers 1979). However, if this increase in order size is accompanied by greater volatility in channel members' effective inventory (negative if carrying backlogs, positive if carrying inventory) then we may have a case of *overreaction*.

For the two POS conditions, Table 8 show the variance of effective inventory for each channel role and demand pattern.

Insert Table 8 about here

Note that being able to see the actual demand for the Step-up pattern helps reduce the variance considerably. Along with the earlier results, it is clear that a better understanding of the one time nature of the change, helps the entire channel improve stability and performance. However, the results are very different for the other two patterns, and especially for the distributor. Reacting too much to far-away information leads to significant inventory buildups followed by significant backlog buildups. Further, it also seems clear that participants have considerably greater difficulty learning how to make decisions under the S-shaped environments (which we had expected to conform more closely with their expectations of demand growth and change), even when they are all able to see the pattern of change.

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 distribution channels, decision oriented research is generally lacking. Building upon Sterman's pioneering work we examined the "Beer Game" under a wider range of circumstances. Specifically, we examined how channel efficiency and individual decision making are 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.

Regarding channel costs and efficiency we find that reducing the cycle time (LAG) results in the greatest positive benefits across all experimental conditions, though the extent of improvement is somewhat mitigated by the pattern of change in customer demand. Surprisingly, we find that making POS information available is unambiguously beneficial in only the simplest scenarios. As the pattern of pattern of change in customer demand becomes more complicated, performance deteriorates. Overall, we find that the basic results reported by Sterman are replicated only for the Step-up demand pattern.

Regarding the manner in which decisions are made and insights into the causes for observed inefficiencies, once again, we find support for Sterman's basic assertion that participants fail to pay sufficient attention to the supply line. But the more complete examination afforded by our experiment also leads to new and refined insights. First, from observing the adjustments made to desired inventory levels as LAG increases, we find that a subject's decision calculus *is* affected by the length of the pipeline, and in a directionally appropriate manner. Rather than finding a systematic bias towards disregarding the supply line we find greater support in favor of a *complexity* argument. As LAG decreases and the supply line gets more predictable (as for the distributor), complexity decreases and the weights participants give to supply line considerations increase.

In addition to the supply line bias and complexity, our analysis uncovered two other sources of inefficient decision making. First, with the availability of POS information, increasing fluctuations in effective inventory and larger distributor costs imply the possibility of *overreaction* by these DMs to less relevant information. Finally, we found that changes in customer demand caused channel members to make separate adjustments to their desired inventory levels. As Lee et. al. (1994) have analytically demonstrated, such lack of *coordination* among channel members can lead to gross inefficiencies of the kind observed in our experiment. Further, contrary to expectations, merely providing shared POS information across the channel does not induce sufficient implicit coordination.

In sum, our results imply that the future research needs to closely examine the individual and joint effects of speeding up the cycle time, improving the communication and coordination among channel members, and reductions in the cognitive complexity of the task through appropriate decision support for individual DMs. Some suggestions for such a research agenda are discussed next.

Future Research

Future research on operational decision making in distribution channels needs to proceed in at least two related directions. First, there is a need to study how ordering and shipping decisions are actually being made in corporations, and the kinds of problems and inefficiencies that are commonly encountered. The other possibility is to expand and enrich the experimental agenda (based, perhaps, on the kinds of observations suggested above). Enriching the "Beer Game" by increasing its external validity, and further exploring the shortcomings of dynamic, interdependent decision making in a controlled laboratory setting is likely to prove beneficial. Our suggestions are in the latter vein.

<u>Overreaction:</u> Our results showed that due to the tendency to overreact, providing more information may not always be beneficial. In our case, more information was operationalized as the availability of POS information. However, more information can also result from more frequent availability of the same data. For example, providing daily rather than weekly POS information is technically feasible. However, if the underlying phenomenon changes at a slower pace, it is possible that DMs might overreact to the noise in day to day information and efficiency might actually suffer. In a series of studies, Wagenaar and Timmers (1978a, 1978b) found that for exponential growth tasks, subjects were better at long range extrapolation with fewer data points (e.g., weekly rather than daily POS data).

To explore this possibility, we conducted a separate "Beer Game" experiment in which half the subjects received 36 periods of "bi-monthly" data, and the other half received 36 period of "monthly" data (following an S-with Error pattern). For the second group, each of the first 18 months of data was the sum of two of the "bi-monthly" sales numbers seen by the first group. Thus, the sum of all 36 periods of demand for the first group, was exactly equal to sum of the first 18 periods of the second groups' demand. *The 36-period total channel costs and forecasting errors for the first group were significantly **higher** than the 18-period total channel costs and forecasting errors for the second group,* in agreement with our conjecture. Faster may not always be better!

Similar over-reaction problems have also been noted in JIT systems under volatile customer demand conditions (Karmarkar 1989, Zipkin 1991). Together with our results, and casual experimental observations, we believe that the *match* between the time it takes for the system to respond to a DM (related to the lag time), the frequency with which information is made available, and the pace with which customer demand is itself changing deserves to be examined in greater detail. We expect, for example, that shorter lead times and more frequent decision opportunities will be most helpful if underlying customer demand is changing rapidly. However, if the period to period change in retail sales are more the result of random variation rather than a basic change in customer needs, shorter lead times and/or more frequent observations should affect channel efficiency adversely. Careful examination of such hypotheses may suggest that the processes developed to deal with one type of demand environment might be predictably inefficient in others.

Complexity: Our results document the gross inefficiencies in decision making created due to the complexity of dynamic interdependent task environments. Future research should now examine how human DMs can learn to operate more efficiently, and how they can be aided in making their decisions.

The vast literature on multiple cue probabilistic learning (MCPL) shows that feedback plays a critical role in learning (Balzer et.al. 1992, 1989, Castellan 1974, Hogarth 1987). In the basic "Beer Game" setup, the only feedback provided to each DM is through incoming orders from the channel member below, and incoming shipments from the channel member above. This type of information is akin to *outcome* feedback (Balzer et. al. 1989, Gupta 1994, Sengupta and Abdel-Hamid 1993). The DM can see what happened, but how and why are unclear. MCPL research shows that outcome feedback alone rarely helps the DM learn in an uncertain environment. Brehmer(1992), and Sengupta and Abdel-Hamid (1993) have found support for this in single-person dynamic decision making tasks. The alternative is to provide cognitive feedback (Balzer et. al. 1989). Cognitive feedback includes information about relations in the task environment, the DM's mental model, and relations between the DM's mental model and the task environment. In the context of the "Beer Game" this would include, for example: information about current and past inventory/backlogs at *other* levels in the channel, information about the length of time it actually was taking for orders to be filled, and information about the particular manner in which the DM was using the three elements in the decision calculus (e.g., displaying the supply line coefficients).

The drawback of providing all of this information is that it could overload the DM's cognitive abilities (Kleinmuntz 1990). Consequently, it is important to investigate what types of cognitive feedback are more effective than others, and how best to present the information. Gupta (1994) and Kleinmuntz and Thomas (1987), among others, have found that providing a *decision aid* which allows the DM to process the available information more readily can prove helpful. Future research on how such aids can be used in the distribution channel context should prove especially beneficial.

Coordination: Our results, and Lee et. al.'s analysis, clearly show that even after speeding up the cycle the need for coordinated decision making remains. Our results also show that merely providing common retail demand information does not significantly improve the results. The role of more explicit coordination needs examination.

From the perspective of upstream channel members, there is a need to account for uncertainty in primary customer demand, and the secondary uncertainty created through the decisions made by downstream members (e.g., are changes in orders from downstream members due to poor decision making, due to a changed policy, or due to other strategic considerations?). Downstream members must deal with uncertainty in incoming orders and the supply reliability of upstream members. Management of these uncertainties through better intra-channel coordination is a hallmark of the partnership arrangements (e.g., Quick Response Systems, Efficient Consumer Response, etc.) emerging in several industries. But, because greater coordination is expensive and requires sharing sensitive information, it is important to understand exactly what aspects must be coordinated and what the resulting benefits are. For example, our results show that compared to improving the lag times, sharing POS information with upstream suppliers is much less effective. However, there is a need to examine whether even greater sharing of information, and perhaps even joint decision making, might result in significant improvements (e.g., by reducing the uncertainty surrounding the strategic intentions of other channel members). Further, research on the contractual aspects of how the benefits of coordinated decision making might be shared among the channel members and how far up the channel such coordination may prove beneficial also need to be examined. The "Beer Game", with variations in the payoff functions, the number of channel members, and opportunities for controlled communications among channel members provides a systematic opportunity for examining these issues.

With the great changes currently underway in relations between vendors and their channel 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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TABLE 1
Are Costs Significantly Different Between LAG Conditions?

	Retailer	*Wholesaler*	*Distributor*	*Channel*
Step-Up	Yes	Yes	Yes	Yes
S, no Error	Yes	Yes	Yes	Yes
S, with Error	Yes	Yes	No	No

TABLE 2
Are Cost Differences Between Channel Member Pairs Significantly Different From Zero?

	LAG=1		*LAG=2*	
	Wholesaler-Retailer	***Distributor-Wholesaler***	***Wholesaler-Retailer***	***Distributor-Wholesaler***
Step-Up	Yes	Yes	Yes	Yes
S, No Error	Yes	No	Yes	Yes
S, with Error	Yes	Yes	Yes	Yes

TABLE 3
Are Costs Significantly Different Between POS Conditions?

	Retailer	*Wholesaler*	*Distributor*	*Channel*
Step-Up	Yes	No	No	Yes
S, No Error	No	No	Yes	No
S, with Error	Yes	No	No	No

TABLE 4
Are Cost Differences Between Channel Member Pairs Significantly Different From Zero?

	POS=n		*POS=y*	
	Wholesaler-Retailer	***Distributor-Wholesaler***	***Wholesaler-Retailer***	***Distributor-Wholesaler***
Step-Up	Yes	Yes	Yes	Yes
S, no Error	Yes	Yes	Yes	Yes
S, with Error	Yes	No	Yes	No

TABLE 5
The Effects of Lag Time Reduction on Supply Line Coefficients (α_{SL})

a) Average Supply Line Coefficients

	LAG=2			LAG=1		
	Retailer	*Wholesaler*	*Distributor*	*Retailer*	*Wholesaler*	*Distributor*
Step-Up	0.00	0.00	0.00	0.07	0.03	0.19
S-no Error	0.00	0.01	0.08	0.00	0.05	0.17
S, with Error	0.01	0.00	0.06	0.02	0.03	0.15

b) Are Differences Between LAG Conditions Significant?

	Retailer	*Wholesaler*	*Distributor*
Step-Up	Yes	No	Yes
S-no Error	No	No	No
S, with Error	No	No	Yes

TABLE 6
The Effects of Lag Time Reduction on Desired Inventory Levels (I^*)

a) Average Desired Inventory Level

	LAG=2			LAG=1		
	Retailer	*Wholesaler*	*Distributor*	*Retailer*	*Wholesaler*	*Distributor*
Step-Up	12.98	137.59	301.59	3.58	114.71	124.32
S-no Error	74.39	123.72	133.84	5.10	44.85	97.03
S-with Error	26.04	100.64	141.16	8.41	102.26	180.83

b) Are Differences Between LAG Conditions Significant?

	Retailer	*Wholesaler*	*Distributor*
Step-Up	Yes	No	Yes
S-no Error	No	No	No
S, with Error	No	No	Yes

TABLE 7
The Effects of POS Information on Average Order Size

a) Average Supply Line Coefficients

	Retailer		*Wholesaler*		*Distributor*	
	POS=n	*POS=y*	*POS=n*	*POS=y*	*POS=n*	*POS=y*
Step-Up	50	47	56	48	65	54
S-no Error	47	55	46	56	48	62
S, with Error	51	56	52	60	56	68

b) Are Differences Between POS Conditions Significant?

	Retailer	Wholesaler	Distributor
Step-Up	No	Yes	Yes
S-no Error	Yes	Yes	Yes
S, with Error	No	Yes	Yes

TABLE 8
The Effects of POS Information on Variance of Effective Inventory

a) Average Variance of Effective Inventory (in units of thousands)

	Retailer		*Wholesaler*		*Distributor*	
	POS=n	*POS=y*	*POS=n*	*POS=y*	*POS=n*	*POS=y*
Step-Up	10	3	41	79	78	199
S-no Error	3	11	21	18	49	16
S, with Error	7	3	34	27	56	30

b) Are Differences Between POS Conditions Significant?

	Retailer	Wholesaler	Distributor
Step-Up	Yes	Yes	Yes
S-no Error	No	No	Yes
S, with Error	No	Yes	Yes

Figure 1
A Traditional Distribution Channel

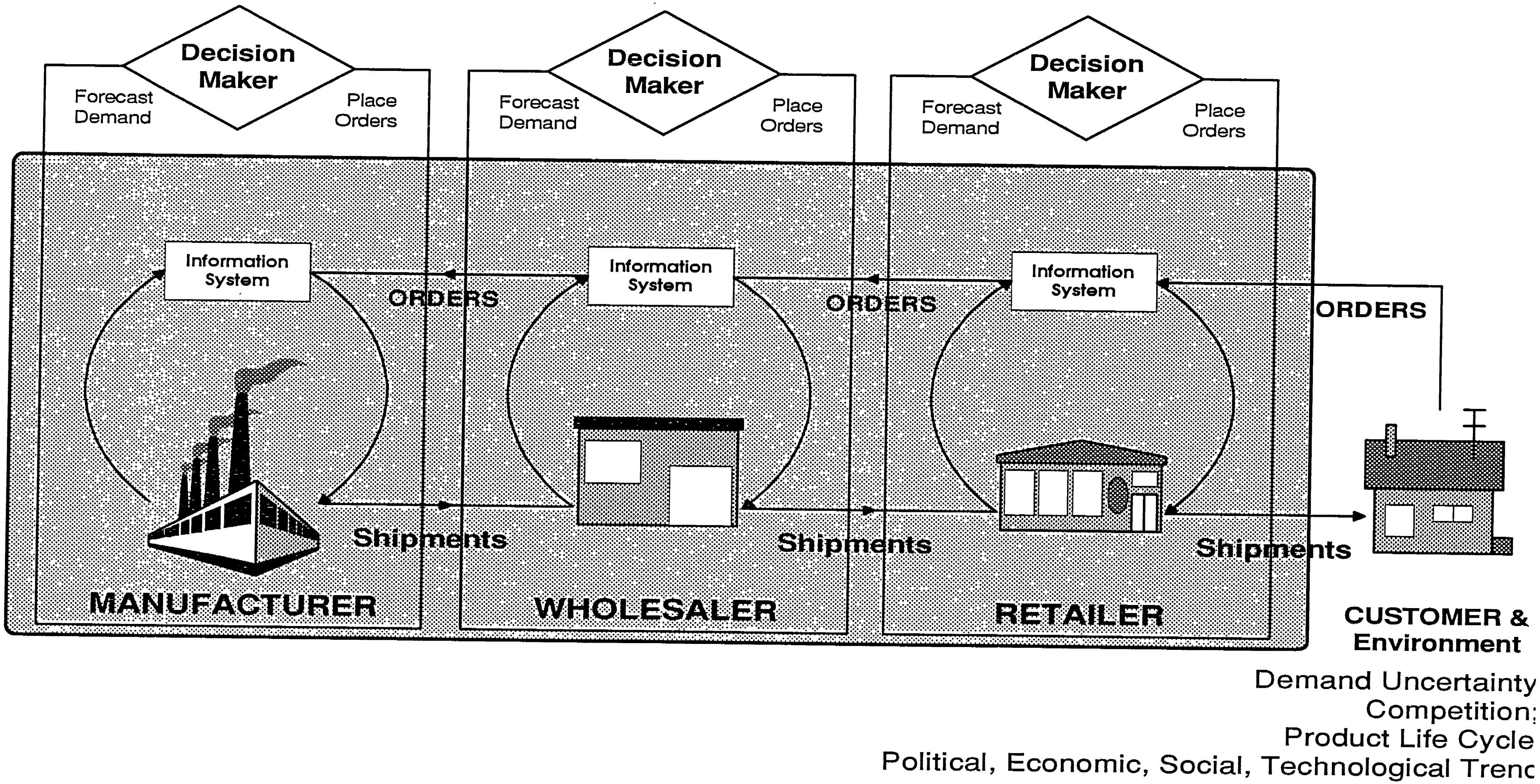

Figure 2
The Typical Beer Game Setup

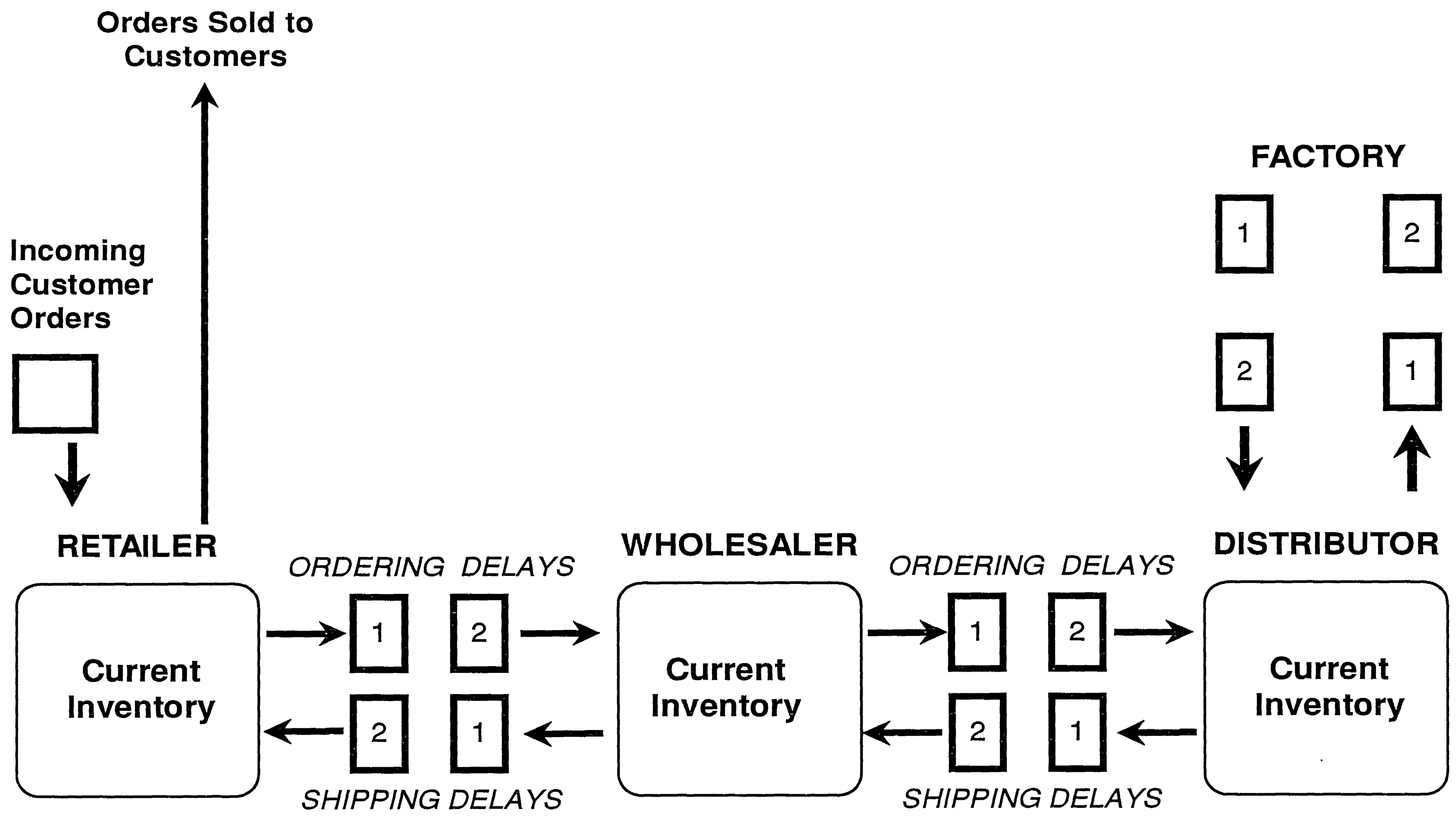

Figure 3
Customer Demand Patterns

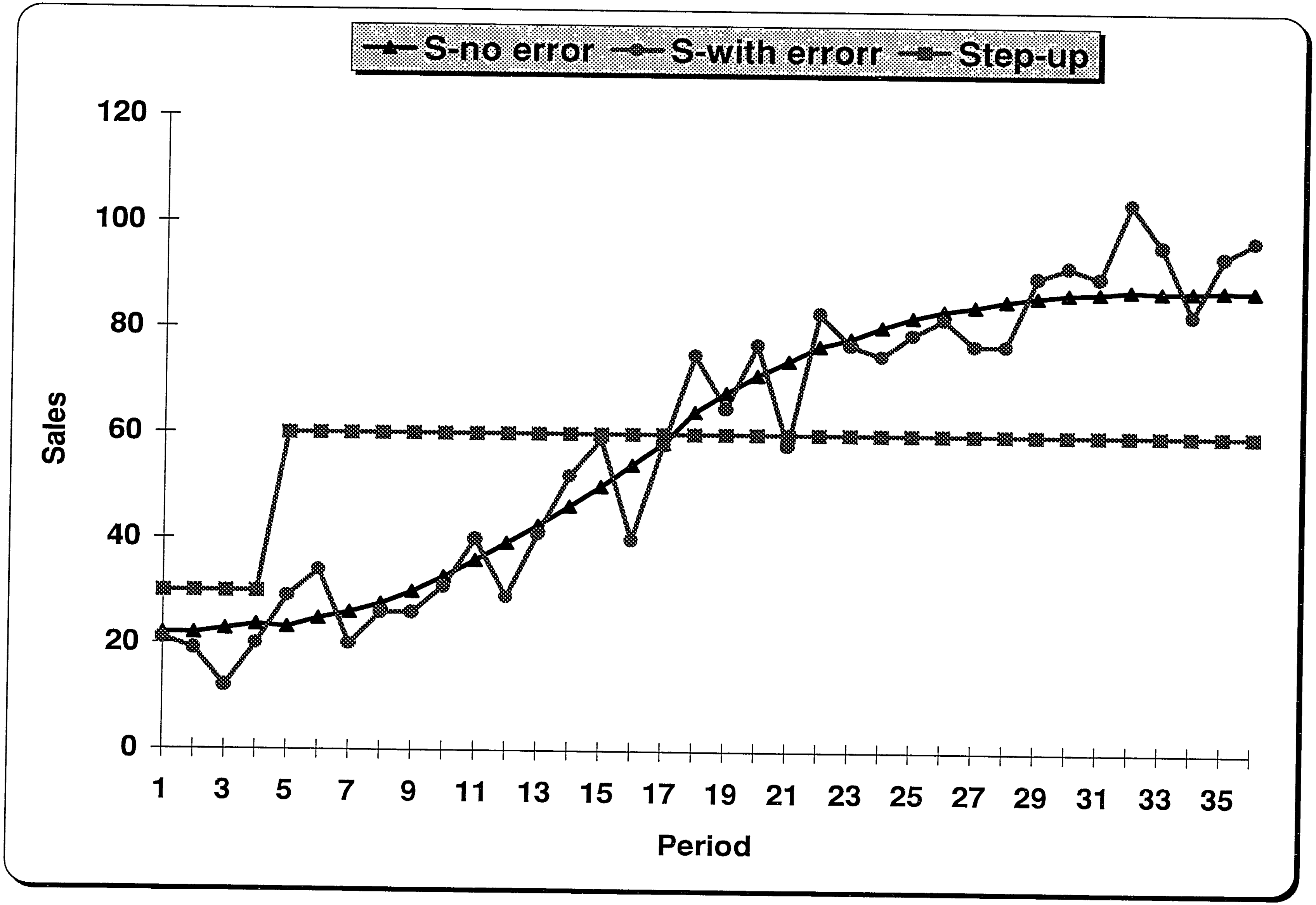

Figure 4

Costs by LAG and Demand Conditions

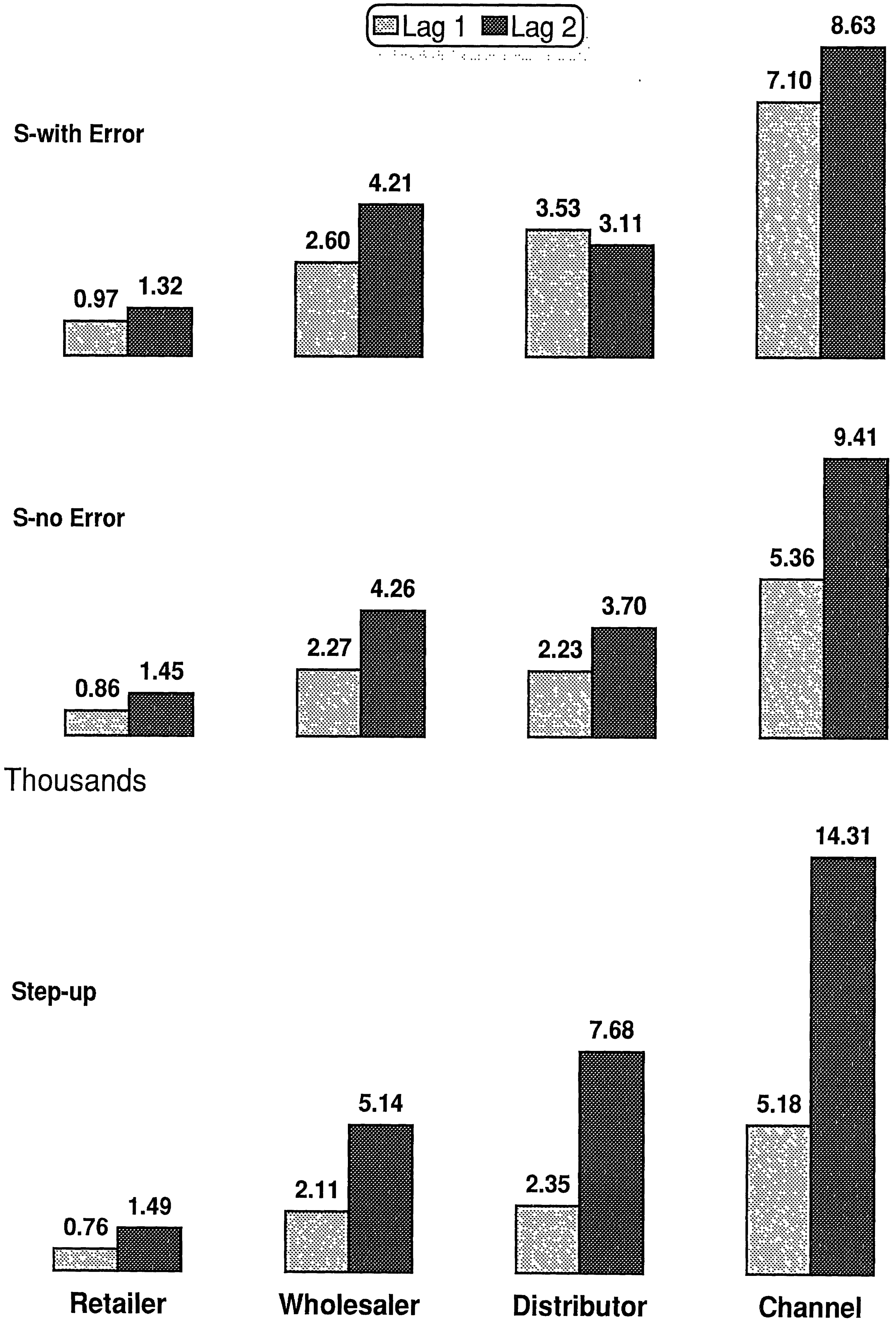

Figure 5

Costs by POS and Demand Conditions