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IMPACT OF POS DATA SHARING ON SUPPLY CHAIN MANAGEMENT: AN EXPERIMENTAL STUDY*

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We examine the impact of point of sale (POS) data sharing on ordering decisions in a multi-echelon supply chain. In particular, we focus on how exposure to POS data may help reduce the "bullwhip effect," the tendency of orders to increase in variability as one moves up a supply chain. Theoretical studies have shown that exposure to POS data can lead to a reduction in the bullwhip effect when suppliers have no prior knowledge of the demand distribution. The benefit of sharing POS data in stable industries, where the demand distribution is commonly known, is less clear. We study this phenomenon from a behavioral perspective in the context of a simple, serial, supply chain subject to information lags and stochastic demand. We find, using a controlled simulation experiment, that sharing POS information *does* help reduce some components of the bullwhip effect in a stable demand setting, namely the order oscillation of upstream members. We offer one possible explanation for this improvement by examining the relationship between order decisions and demand line information.
(BULLWHIP EFFECT; SUPPLY CHAIN MANAGEMENT; POS DATA; EXPERIMENTAL ANALYSIS)

1. Introduction

Procter and Gamble first coined the phase "bullwhip effect" to describe the ordering behavior witnessed between customers and suppliers of Pamper Diapers (Lee, Padmanabhan, and Whang 1997). While diapers enjoy a fairly constant consumption rate, Procter and Gamble found that wholesale orders tended to fluctuate considerably over time. They also found that the orders placed to their suppliers for raw materials exhibited even larger fluctuations than wholesale orders. Other companies have observed a similar tendency in their internal supply chains (Baljko 1999a, 1999b).

The effect itself is described by two regularities; *oscillations* of orders at each level of the supply chain and the *amplification* of these oscillations as one moves farther up the chain. Both oscillation and amplification are costly to supply chains. Baganha and Cohen (1998) provide empirical evidence of these problems in industries with high-order variation, while Kahn (1987) offers a macroeconomic view of the relationship between order volatility, inventory, and cost.

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Previous analytical research suggests a number of strategies for reducing the bullwhip effect (e.g., see Lee et al. 1997). One of the most cited remedies is to transmit point of sale (POS) data to upstream suppliers. Theoretical studies (e.g., Chen, Ryan, and Simchi-Levi 2000; Chen, Drezner, et al. 2000) show that exposure to POS data can lead to a reduction in the bullwhip effect when suppliers have no prior knowledge of the demand distribution. In such a setting, exposure allows upstream members to learn the structure of the demand distribution more quickly and effectively reduces the order lead-time between levels of the chain.

The benefits of sharing POS data when the demand distribution is stable and commonly known are less clear. This setting is representative of products, such as basic hardware, diapers, grocery, and pharmaceutical goods, with stochastic, but relatively stable, retail demand. On the one hand, theory (e.g., Chen 1999) claims that the bullwhip effect should not exist in this setting and (thus) sharing POS data should not lessen its effect. In practice, however, many firms have instituted these systems in such settings, often at great expense. For example, Home Depot now uses POS scanning systems to collect data on everything from ten-penny nails to deck coating. Home Depot shares this data with 400 of its highest volume vendors, with more expected to follow in coming years. Since this type of system installation is often accompanied by changes in warehouse, shipping, and replenishment policies, it is difficult to measure empirically what fraction of improvements (if any) is due to POS data visibility itself. Experimental research offers a means for studying this change in isolation. This is precisely our goal in this paper.

We report on the results of two controlled experiments comparing human ordering behavior, with and without access to POS data, in a simple serial supply chain subject to information lags. These experiments provide a middle ground between analytical theory and practice by exploring the impact of POS sharing on bullwhip behavior in a controlled environment. Our results show that sharing POS information does reduce some components of the bullwhip effect, particularly the order oscillations of upstream members. This supports the notion that upstream chain members stand to gain the most from information-sharing initiatives, as suggested by several analytical studies of two echelon systems (e.g., Bourland et al. 1996; Cachon and Fisher 2000; Gavirneni et al. 1999). It also is consistent with recent behavioral research on the impact of inventory information sharing on supply chain performance (Croson and Donohue 1999). Because order oscillations are significantly lower at upstream levels when POS data are shared, we also find that order amplification is not reduced uniformly. In our four-echelon supply chain, only the middle link (between wholesalers and distributors) exhibits a significant reduction in amplification.

Looking deeper at how POS data relate to order decisions at the individual level, we regress individual ordering decisions on POS data and internal orders. The results are a "best fit" model of what information individuals consider when placing their orders. When POS information is available, chain members appear to weigh this information highly in their order decisions. In contrast, internal orders receive less weight in explaining or predicting decisions once POS data are available. This supports the empirical observation that when POS data are shared with upstream suppliers, supplier-managed inventory initiatives often follow. As the reliance on (and thus the benefit of) passing internal orders reduces, suppliers push toward managing the inventory replenishment process themselves, rather than relying on downstream chain members' decisions.

These results complement contemporaneous experimental studies on the impact of POS data sharing in settings where the demand distribution is *unknown* to suppliers and non-stationary. Gupta, Steckel, and Banerji (2002) and Steckel et al. (2002) examine the impact of sharing POS data on supply chain costs (rather than order behavior) when the unknown and non-stationary demand distribution follows one of three processes, including a step function and a S-shaped function with or without error. Since the experimental design involved unknown and non-stationary demand functions and the authors did not analyze ordering behavior, their results cannot be conclusively attributed to behavioral causes. However, it is interesting that the placement of the "improvement" in these cases favored players at the beginning of the supply chain. In fact, exposure to POS data actually increased costs for upstream levels in some cases. Our results, in contrast, suggest that in more stable demand settings (where the underlying demand distribution is stationary and known) it is the players near the end of the line that stand to gain the most from POS data sharing.

Other researchers have studied behavioral aspects of the bullwhip effect without explicitly examining the effect of POS sharing systems. Sterman's (1989) paper was the first to identify behavioral causes of the bullwhip effect in an environment where the demand distribution is unknown to participants. Croson and Donohue (1999) build on this research by confirming that behavioral factors still exist when participants are aware of the underlying demand distribution. They also examine the impact of instituting a chain-wide inventory tracking system. Their results are similar to those reported here. Passing of real time information (in their case, inventory information; in our case, POS information) reduces order fluctuations across the supply chain with the majority of the improvement seen at upstream supply levels.

While our focus is on behavioral causes of the bullwhip effect, it is worth noting the growing literature examining operational causes. Lee et al. (1997) outline the most common causes, including order batching, price fluctuations, supply shortages, and demand signal processing. They also provide simple remedies for eliminating their impact. Baganha and Cohen (1996) analyze the impact of order batching on order variance and inventory using a simulation model. Caplin (1985) shows that (S, s) policies can contribute to the bullwhip effect when used by multiple retailers served by a common supplier. He finds that the magnitude of order oscillations increases with the average retail order size. Meixell (1998) and Graves (1999) analytically examine the relationship between order variance and batch size. Interestingly, Graves' explicit expression for the magnitude of amplification appears independent of the level of information provided to upstream stages. Sogomonian and Tang (1993) examine the benefits of a stable retail price strategy (i.e., everyday low price) on supply chain cost. Cachon and Lariviere (1999) examine the impact of perceived supply shortage on ordering behavior in a two-echelon supply chain and propose supply allocation policies to eliminate retail order gaming. Finally, Chen, Ryan, and Simchi-Levi (2000) and Chen, Drezner, et al. (2000) quantify the impact of demand signal processing and lead-times on the variance of orders throughout a supply chain, using a variety of demand forecasting techniques. In the experiment reported here, we control for these operational factors to focus purely on the behavioral impact of POS data sharing.

The paper continues in Section 2 with a description of our experimental setting. Section 3 describes our hypotheses and statistical results. Section 4 discusses the study's main results and their implications for industry and future research and Section 5 provides final conclusions.

2. Experimental Design and Implementation

We follow the previous experimental research of Sterman (1989), Gupta et al. (2002), Steckel et al. (2002), and Croson and Donohue (1999) by conducting experiments within the context of the Beer Distribution Game, first created by Forrester (1958). The game mimics the mechanics of a decentralized, periodic review, supply chain with four, serial echelons. Each echelon is controlled by a different player i, $i = 1, \ldots, 4$. Each participant places orders to his upstream supplier and fills orders placed by his downstream customer, over a series of time periods (e.g., weeks) $t = 1, \ldots, T$. Figure 1 provides an illustration of the supply chain.

The game is complicated by the existence of order processing and shipment delays between each supplier/customer pair. Once an order is specified, two time periods pass before the order actually arrives to the supply site. Similarly, once an order is filled, two time periods pass before the shipment arrives to the downstream customer. At the highest echelon level ($i = 4$), orders represent production starts and therefore require a different type of delay. In

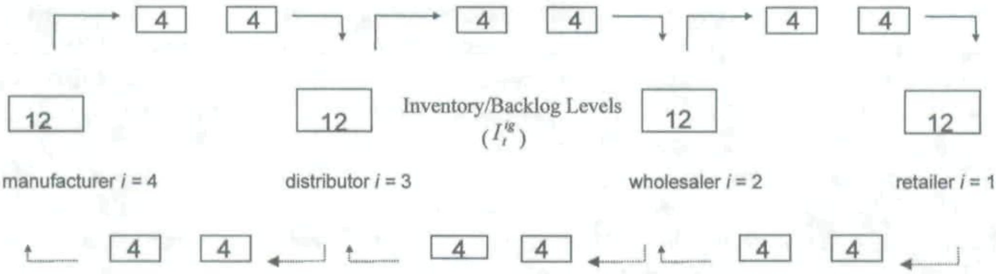

FIGURE 1. Distribution System Used in the Beer Distribution Game.

keeping with the traditional Beer Distribution Game setup, we assume three time periods are needed to process and manufacture an order.

Each period t begins with the arrival of shipments from a participant's upstream supplier. After adding these shipments to inventory, new orders from the participant's downstream customer are processed (for the retailer, these orders are simply retail demand sold to consumers at a fixed price). These orders are filled and shipped from current inventory, while any excess demand is placed in backlog. At the end of the period, participants place an order with their upstream supplier. These orders are the decision variables of interest in the game. Our analysis focuses on how the oscillation and amplification of these orders change with the availability of POS information.

The supply chain setting described so far eliminates three of the four operational causes of the bullwhip effect cited by Lee et al. (1997): inventory allocation (since there are no competing customers and manufacturing capacity is infinite), order batching (since setup times are zero), and price fluctuations at the retail level (since prices are constant over time). We controlled for the fourth operational cause (demand signal processing) by announcing the demand distribution to all supply chain members before beginning the game. This demand was uniformly distributed between 0 and 8 and independently drawn between periods.

We developed a web-based software package to run the game, where each member of the supply chain works off a separate computer. We followed the protocol of Croson and Donohue (1999) in instructing participants and assigning them to roles. Participants were informed they would be paid according to a continuous incentive scheme, based on their group's cumulative chain costs. The scheme provided a base compensation of \$5 for each participant along with a bonus of up to \$20 per participant based on their supply chain's costs relative to those of other chains. The bonus for each member of group g was calculated as follows, based on the cumulative cost of the chain C^g,

$$b^g = \$20 \frac{\max_g (C^g) - C^g}{\max_g (C^g) - \min_g (C^g)}$$

Chain cost in each period was defined as the sum of inventory holding and backlog cost across all four supply levels. Participants were told they would incur unit holding costs of \$0.50, and unit backlog costs of \$1 per period. Croson and Donohue (1999) used these same parameters and corresponding incentive scheme when studying the impact of sharing inventory information across a supply chain. Details about the scheme and its benefits are spelled out in that paper. Briefly, the scheme implies that each member of a given group has the same goal, to minimize channel costs, while having the freedom to make their own inventory decisions.

Participants were told that every level of the supply chain would begin with initial inventory level of 12, outstanding orders of 4 for the last two periods, and incoming shipments of 4 in the next two periods (as depicted in Figure 1). Participants were not informed how many periods the experiment would run to avoid end-of-game behavior that might trigger over- or under-ordering. The actual number of periods was $T = 48$ for all experimental sessions. All sessions also used the same random number seed to generate consumer demand, to control for variation due to different demand streams.

3. The Experiment

To examine the effect of POS data on behavior, we ran the experiment under two treatments. In the control treatment, all participants knew the distribution of retail demand but only the retailer ($i = 1$) observed actual retail demand. In the POS treatment, all participants knew the underlying demand distribution *and* observed actual retail demand in each period through a time plot, which was dynamically updated in each period. The experiment involved a total of 84 participants divided into groups of four, with 11 groups in the control treatment and 10 groups in the POS treatment. Participants were drawn from business students at the Carlson School of Management enrolled in an OM course during Spring 2002.

3.1 *Hypotheses*

Previous researchers have shown analytically that rational decision-makers will induce the bullwhip effect when the demand distribution is either non-stationary (Lee et al. 1997) or unknown (Chen, Ryan, and Simchi-Levi 2000; Chen, Drezner, et al. 2000) to upper echelon supply chain members. If the demand distribution is both stationary and commonly known, theory suggests that no bullwhip effect will exist (e.g., see Chen 1999). However, in a recent experimental study, Croson and Donohue (1999) show that participants do exhibit the bullwhip effect when reacting to a known and stable retail demand distribution. Since all operational factors were removed from the experimental setting, this result suggests that other, behavioral factors, also contribute to bullwhip behavior.

Whether exposure to POS data will alleviate these behavioral factors is an open question. Without POS data, participants have to gauge how much of their customer's order is due to real demand for the product, and how much is due to other factors, such as their customer's inventory position, expectations of future demand, or other distortions. The addition of POS data may improve chain members' ability to predict future order quantities and thus better respond to random fluctuations in demand. If the ordering process is improved in this fashion, the two following effects may result: (1) order oscillations will decrease at each supply chain level, and (2) amplification of these oscillations will reduce between levels. This leads to two hypotheses about the effect of POS data.

HYPOTHESIS 1. *Sharing POS information across the supply chain will decrease the magnitude of order oscillations within supply chain levels.*

HYPOTHESIS 2. *Sharing POS information across the supply chain will decrease the magnitude of amplification of order oscillation between*

a) *Retailers and Wholesalers*;
b) *Wholesalers and Distributors*;
c) *Distributors and Manufacturers.*

Additionally, we hypothesize that the impact of POS data will be larger for upstream members of the supply chain (e.g., the manufacturer and the distributor) than for downstream members (e.g., the retailer and the wholesaler). As we move upstream (farther from the retail site), there is potentially a greater distortion between the orders a supplier sees and actual retail demand. Therefore, we conjecture that POS data have a greater opportunity to alter orders at upstream positions. In the extreme case of the retailer, no new demand information is provided by POS data. Some change in retail behavior is possible if the retailer is affected by changes in the ordering behavior of other members (e.g., if upstream members can fill orders more promptly), but we predict this second-order change will be less significant. This reasoning leads to our last hypothesis.

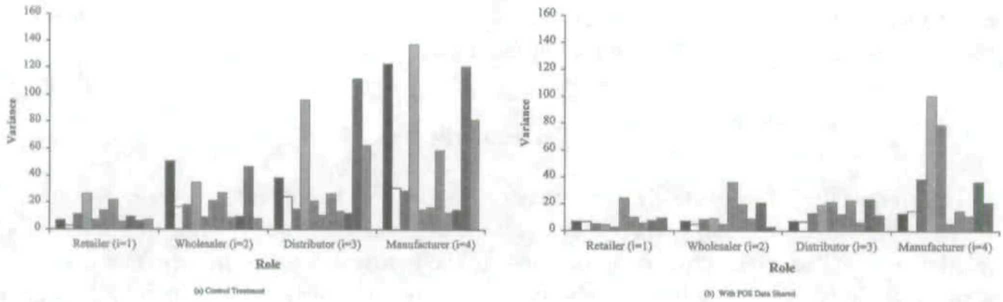

FIGURE 2. Variance of Orders, by Role and Group, for Each Treatment.

HYPOTHESIS 3. *Sharing POS information across the supply chain will lead to a larger reduction in order oscillations for manufacturers and distributors than for retailers and wholesalers.*

3.2. *Impact of POS Data: Experimental Results*

Figure 2 graphs the variance of orders placed in the control and POS treatments. Visual inspection of these data provides initial support for our three hypotheses. The variances of orders appear to decrease between the control and POS treatments, as does the amplification of those variances. The decrease also appears to be largest for distributors and manufacturers.

Oscillation Comparison

To test whether POS data offer some benefit in reducing the order oscillation component of the bullwhip effect compared with the control treatment, we perform a two-tailed Mann–Whitney U test (also called the Wilcoxon test, see Seigel 1965, page 116). This test compares the variance of orders across the two treatments. The Mann–Whitney U test is a nonparametric test, so it does not rely on any data distribution assumptions. This is particularly important in our setting, as our data are not normally distributed (in particular, by definition all the observations of order variance are positive). The test returns a test statistic, U, based on the rank-order of the data in the two samples (the variances in the two treatments). In combination with the sample size (n and m), this generates a z-statistic (z) and associated significance level (p). The data in this case reveal that order variances are significantly less when POS data are commonly known ($n = 44$, $m = 40$, $U = 571.5$, $z = 2.763$, $p = 0.003$), supporting Hypothesis 1.

Amplification Comparison

To test whether the bullwhip effect is completely eliminated once POS data are known, we perform a nonparametric sign test (see Seigel 1965, p. 68 and Table D). This test measures whether or not order amplification exists by coding an increase in the variance of orders placed between roles, for a given supply chain, as a success and a decrease as a failure. Our data revealed a 83% success rate when POS data are shared, which is significantly different than the 50% success rate expected in a supply chain with no order amplification ($N = 30$, $x = 5$, $p = 0.003$). Order amplification appears to still exist despite participant's access to POS information.

We next compare the extent of amplification across treatments to see whether sharing POS data damps its effect, as suggested by Hypothesis 2. We measure order amplification here as a ratio of the order variance at adjacent roles (e.g., the variance of a wholesaler's orders divided by the variance of his retailer's orders). We then use a Mann–Whitney U test to detect whether these ratios change across treatments for each supplier/customer pair.

The data reveal that significantly less amplification occurs between the wholesaler and distributor when POS data are shared ($n = 11$, $m = 10$, $U = 26$, $z = 2.042$, $p = 0.021$), consistent with Hypothesis 2b. However, there is no significant impact on the amplification observed between either the retailer and wholesaler ($n = 11$, $m = 10$, $U = 53$, $z = 0.141$, $p = 0.440$) or the distributor and manufacturer ($n = 11$, $m = 10$, $U = 38$, $z = 1.197$, $p = 0.116$), not consistent with Hypotheses 2a or 2c.

In interpreting these amplification results, note that amplification reduction is not as direct a measure of supply chain improvement as oscillation reduction. For example, if order oscillation decreased in a consistent fashion (for example, by a common factor) at each supply level, there would be no amplification improvement. However, this oscillation improvement would still signify a significant reduction in inventory and backorder costs. By only revealing significant amplification reduction between the wholesaler and distributor, our results seem to suggest that the magnitude of oscillation reduction is fundamentally different between the front and back end of the supply chain. We formally test this conjecture next.

Asymmetric Reductions in Oscillation

Hypothesis 3 predicts that the impact of POS information will increase the farther one moves from the retail site. To measure the size of this decrease, we calculate the ratio of the variances between the POS and the control treatments ($\sigma^2_{POS}/\sigma^2_{Control}$) for the upstream and downstream roles. Ratios of less than one indicate decreased order oscillation in the POS treatment. These ratios are 0.66 for the retailers and wholesalers, and 0.48 for the distributors and manufacturers, indicating a larger improvement for upstream members than downstream members. To test our hypothesis that upstream members' oscillations reduce more, we perform a Mann–Whitney U test separately on the order variance of downstream (retailer and wholesaler) and upstream (distributor and manufacturer) chain members.

The data reveal no significant difference in order oscillation for the retailer and wholesaler across treatments ($n = 22$, $m = 20$, $U = 104$, $z = 0.211$, $p = 0.416$). However, it does find significantly lower oscillation for the distributor and the manufacturer when POS data are shared ($n = 22$, $m = 20$, $U = 128$, $z = 2.317$, $p = 0.010$). This result supports Hypothesis 3 and is consistent with our mixed amplification results.

3.3. *Information Weighting: How Are POS Data Used?*

Our results so far suggest that exposure to POS data reduces order oscillation at higher levels of the supply chain. However, it is still not clear why this is the case. Specifically, how might upstream players use this new information to reduce their order variation? To help answer this question, we consider two types of information an individual may take into account when placing an order: their *supply line* and their *demand line*.

Previous research on the Beer Game demonstrates that participants often underweight their supply line when placing orders (Sterman 1989, Gupta et al. 2002, Croson and Donohue 1999). Subjects in these experiments fail to account for outstanding orders in assessing their current inventory position. We conjecture that sharing POS information will not counteract this tendency since it provides no additional supplier-based information.

The existence of a bullwhip effect may also imply that participants overreact to the orders they receive from their downstream customers (their demand line), by placing orders with higher volatility than those they receive. In exploring how participants weigh their demand line, we are interested in the impact of the orders they receive versus actual retail demand on their ordering decisions. We conjecture that sharing POS information leads to a reduced focus on internal orders and an increased focus on POS information in the order decision.

We investigate these questions, following Sterman (1989), by regressing individual ordering decisions on various factors one might consider in choosing these orders. Thus for each individual we calculate the "best fit" model—the model that best explains and predicts his ordering decisions. Of course, without getting inside the mind of the participant, we cannot conclude that he actually chooses his orders according to this model. Nonetheless, our data can examine what information, weighted in what fashion, best describes and predicts individuals' decisions.

Supply Line Results

To test how subjects treat their supply line, we ran the following regression

$$O_t^{ig} = \max\{0, \alpha_0 + \alpha_I I_{t-1}^{ig} + \alpha_R O_{t-2}^{i-1,g} + \alpha_S S_t^{ig} + \alpha_N N_t^{ig} + \alpha_t t + \epsilon\} \quad (1)$$

separately for each role i and group g, where $O_t^{i,g}$ is the participant's order in period t. The independent variables include the participant's inventory position last period (I_{t-1}^{ig}), orders received from their downstream customer in the current period ($O_{t-2}^{i-1,g}$), shipments received from their upstream supplier (S_t^{ig}), and the total orders they have outstanding in their supply line ($N_t^{ig} = 0_{t-1}^{i,g} - \min\{0, I_t^{i+1,g}\} + S_t^{i-1,g} + S_{t-1}^{i+1,g}$) . The regression also controls for time trends and individual effects. The max function reflects that all orders must be non-negative. Note that N_t^{ig} represents all orders a participant has placed to date with their upstream supplier that have not yet arrived. If the subject is correctly weighting his supply line, outstanding orders should be weighted the same as current inventory. In terms of our regression, this implies $\alpha_{\mathrm{I}} = \alpha_{\mathrm{N}}$.

We ran this regression for all 84 subjects and found they were highly significant overall. The average R^2 statistic was 0.66. Only three subjects' F-statistic indicated their choices could be equally well explained by a constant order amount. If subjects were not underweighting the supply line, the coefficient on inventory (α_{I}) should be neither higher nor lower than the coefficient on outstanding orders (α_{N}). We found that α_{I} was lower than α_{N} for 39 of 40 subjects in the POS treatment, and for all 44 subjects in the control treatment. This difference is statistically significant ($p < 0.001$, using a binomial test), which supports our initial conjecture. Subjects continue to underweight the supply line, even when POS information is shared.

Demand Line Results

To test how subjects treat their demand line, we ran a new series of individual regressions to compare the relative weighing of retail and immediate customer demand. Our regression compares relative weights on inventory in the previous period (I_{t-1}^{ig}) , orders received in the current period (OR_t^{ig}), and realized demand in the current period (D_t^{ig}). The regression equation is thus

$$O_t^{ig} = \max\{0, \alpha_0 + \alpha_I I_{t-1}^{ig} + \alpha_R OR_t^{ig} + \alpha_D D_t^{ig} + \alpha_t t + \epsilon\} \quad (2)$$

This regression was run on all participants except those assigned to the role of retailer, for whom orders received and realized demand are identical. Overall these regressions were highly significant. The average R^2 (adjusted) statistic over all regressions was 0.66, with no subjects' choices equally well explained by a constant order amount. One concern with this regression is the possible correlation of demand and orders received at lower levels of the supply chain (such as wholesalers). The effect of any correlation is to increase the standard error of the estimates, making it less likely to find significant results. Thus our regression is a conservative test of the relationship between orders and the demand line; one would expect higher significance if the data were perfectly uncorrelated.

In the control treatment we found subjects relied heavily on the orders they received in placing their own orders. The average coefficient on orders received (α_{R}) for these 33 regressions was 0.57, with 97% of subjects placing a higher weight on orders received than on current POS demand (α_{D}). In contrast, in the POS treatment, subjects relied almost equally on both the orders they received and the retail demand in the current period to make their ordering decisions. In this treatment, coefficient averages were $\alpha_{\mathrm{R}} = 0.39$ and $\alpha_{\mathrm{D}} = 0.36$, with only 56% of subjects placing a higher weight on orders received than demand. The interesting result here is not that subjects do not use POS data when it is not available (i.e., in the control treatment), but that they *do* appear to use it when it is available.

For a more direct look at how POS data are used across supply levels, we calculate the relative reliance each individual places on POS information versus their orders received (i.e., the ratio of coefficients α_D and α_R). This ratio is significantly higher among distributors and manufacturers (averages of 1.37 and 2.31, respectively) than among wholesalers (0.76). In placing an order, manufacturers and distributors weight POS information nearly twice as high as internal orders. In contrast, wholesalers place orders *as if* they are weighting internal orders slightly more than POS information. It appears that the roles relying most heavily on demand data are exactly those showing the most reduction in oscillation (i.e., the distributor and manufacturer). Of course, without actually getting inside the player's mind, we cannot know if they are actually using POS data and internal orders to make their ordering decision. Regressions, however, can tell us that they are placing orders as if they are weighting these pieces of information in this way. That is, the model that best explains and predicts their ordering behavior involves weighting POS data and orders placed as described.

Since the addition of POS data did not affect how participants reacted to their supply line but did change reactions to the demand line, we conjecture that it is this change in behavior that reduces order oscillation at higher levels of the supply chain. This implies that the value of sharing POS data is its ability to enable upstream supply chain members to better interpret their demand line, and to choose the orders they place taking into account not only the orders placed to them but also information conveyed by POS data. We conjecture that it is this improved decision-making process, particularly at upper echelon levels, which comprises the behavioral benefits of POS sharing systems.

4. Discussion of Results

The experiments reported in this paper investigate the behavioral impact of adding POS data-sharing to supply chains. Results indicate that the addition of this data significantly improves performance of supply chains by reducing order oscillation consistent with hypothesis 1, particularly at higher levels in the chain (distributor and manufacturer) consistent with hypothesis 3. This reduction of oscillation at higher levels of the supply chain leads to reduced amplification between the two middle levels (that is, between the wholesaler and the distributor) but not between the other levels. Thus the data support hypothesis 2b but not hypothesis 2a or 2c.

To put this in context, it is important to remember that most gains of POS sharing systems have been attributed to *operational* improvements that favor upstream supply levels. Our research shows that POS data sharing offers *behavioral* advantages as well and that these benefits also favor upstream levels. This result raises several interesting conjectures about the effective implementation of POS data sharing systems. First, since higher echelons have the most to gain from POS data sharing initiatives, we expect such initiatives to be most beneficial when these higher level suppliers are involved. Second, for companies wishing to invest in EDI technology, we conjecture that sharing POS data with the highest echelons will provide the "biggest bang for the buck" to the supply chain as a whole. Indeed, it appears that it is these players who act as if they are using POS data, by weighting it most heavily in their order decisions. Third, since higher echelons have the most to gain from POS data sharing, we conjecture that these echelons will be the most in favor of such a sharing initiative and perhaps will be most likely to fund them. Further empirical work is clearly needed to test the accuracy and applicability of these conjectures.

Our analysis at the individual level investigated how decision-makers use their supply and demand lines in the presence of POS information. We found, as expected, that subjects continue to underweight their *supply line* in their ordering decisions whether or not POS data are known. However, subjects did react differently to their *demand line* in the presence of POS data. In particular, when POS data are available, participant's orders are best explained by a weighted average of the orders they receive from their downstream customer and observed retail demand. We found that the roles exhibiting the greatest reduction in order oscillation also placed greater weight on the demand signal (i.e., POS data) relative to the internal orders they receive.

This analysis suggests the mechanism by which POS data can help (or possibly hurt) performance in supply chains and to organize the previous results of Gupta et al. (2002) and Steckel et al. (2002). When demand is stationary and known (as in our study), sharing POS data can help reduce the bullwhip and associated supply chain costs by helping upstream suppliers better anticipate their customers' needs without biasing their estimates of future demand. In contrast, when the distribution of consumer demand is non-stationary and unknown (as in Gupta et al. and Steckel et al.), additional information such as POS data can bias upstream participants' estimates of future demand, which can increase (rather than decrease) costs at upstream levels. Since Gupta et al. (2002) and Steckel et al. (2002) focused on cost, rather than order behavior, it remains unclear whether the cost increase in their case is caused by the bullwhip effect or some other behavioral phenomena. For example, it may be that players simply increase their safety stock, leading to higher inventory costs even if their order variances remain unchanged.

These individual results have implications for operations practice as well. Implementing a POS data sharing system is often the first step toward developing a vendor-managed inventory program. Our results suggest that this transition is quite natural from a behavioral perspective. The decreased weight placed on internal orders by upper echelon players, when POS data are available, is consistent with a movement toward vendor-managed inventory, where suppliers make replenishment decisions with little or no reliance on immediate customer orders. In our study, this behavioral change occurred naturally with no prodding from outside forces.

5. Conclusions

Most high-volume retailers are now capturing POS data in electronic format. Such information is becoming readily available and, in some cases, is being shared with upstream supply chain members. Our experimental results demonstrate that sharing POS data can lead to savings in settings where decision-makers are prone to decision bias. In particular, we find that such information sharing reduces order oscillation at higher levels of the supply chain by allowing those members to better interpret the internal orders they receive. This is encouraging for companies within these industries who are contemplating (or enacting) EDI initiatives.

We believe that experiments can provide an important and interesting new tool for examining operations management questions, particularly those that rely on human decision-makers who may be biased or have other cognitive limitations. Future research in this area might examine the robustness of our results on information sharing in different supply chain settings (e.g., service-oriented supply chains as in Anderson and Morrice 2000) or under different demand distributions (e.g., non-stationary, seasonal, different coefficients of variation). One could also examine the robustness of the results to varying costs of overage and underage, or different order and shipment lags. Additionally, more work investigating the impact of individual specific traits (e.g., previous training or personality characteristics such as patience or analytic ability) would enable one to draw conclusions about the types of characteristics and training that produce successful outcomes. Overall we believe human experiments will continue to grow as an important methodology for understanding decisions critical to operations managers in the years to come.[1]

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