

# The impact of ordering behavior on order-quantity variability: A study of forward and reverse bullwhip effects

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We test the effects of various ordering behaviors in a serial supply chain subject to random supply disruptions. We find that the bullwhip effect (BWE) does not occur in all cases, especially during disruptions. Moreover, we find evidence of a reverse bullwhip effect (RBWE), in which order variability increases as one moves downstream in the supply chain. We test these phenomena using both a live “beer game” experiment and a simulation study. In the beer game, we find that players modify their ordering habits during disruptions, and that these modifications lead to the RBWE. We confirm this cause of the RBWE under a broad range of settings using simulation. Our results confirm previous studies showing that demand uncertainty and an underweighting of the supply line causes the BWE. Moreover, they demonstrate that supply uncertainty (in the form of random disruptions) and an overweighting of the supply line causes the RBWE.

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## 1. Introduction

The bullwhip effect (BWE) describes the amplification of order variability as one moves upstream in the supply chain. The BWE was formally introduced and analyzed by Lee et al. [23], and has since drawn extensive attention from both academia and industry. However, recent evidence suggests that the BWE does not prevail in general. Baganha and Cohen [3] study the quantity of shipments from manufacturers and that of sales from wholesalers and retailers in the USA from 1978 to 1985. They conclude, by examining the coefficient of variation, that it is the wholesalers rather than the manufacturers who see the largest variance of demand (i.e., orders from retailers). This implies that the wholesalers actually

smooth the orders received from the retailers rather than amplifying them. Moreover, Cachon et al. [7] perform a detailed empirical study at the industry level and show that only 47% of industries studied exhibit the BWE, while the remaining 53% show the reverse.

Similarly, although a number of studies have confirmed the presence of the BWE in an experimental setting using the well known “beer game” [9, 11, 12, 13, 14, 19, 28, 36, 41], several of these studies [12, 13, 14, 19, 41] find a substantial portion of trials in which the opposite effect occurs.

In this paper, we use beer game and simulation experiments to test the ubiquity and magnitude of the BWE when random supply disruptions are present. When supply is uncertain, we find evidence of a *reverse bullwhip effect* (RBWE), in which order variability increases as one moves downstream in the supply chain. As a general claim, we can say that demand uncertainty tends to cause the BWE, while supply uncertainty tends to cause the RBWE. However, both of these tendencies are subtly influenced by players’ ordering behaviors, which we explore in much greater detail below.

## 1.1 Anecdotal Evidence for the RBWE

Consumer purchasing behavior following hurricanes Katrina and Rita in 2005 provides anecdotal evidence of the RBWE. Information Resources Inc. (IRI) [1] provides sales data for consumer packaged goods (CPG) across the United States between the landfalls of the two hurricanes and finds a significant fluctuation in demand for certain products, such as food and water, during this time. This suggests that demand volatility is greater than supply volatility—the reverse of the BWE.

A *Wall Street Journal* article from the time [16] describes similar patterns in gasoline buying:

Typically, car tanks are about one-quarter full. If buyers start keeping car tanks three-quarters full, the added demand would quickly drain the entire system of gas supplies. Dan Pickering, president of Houston-based Pickering Energy Partners, says: “What you don’t have in the system is the ability to run every car full of gas. If you get a hoarding mentality among the consumers, then it tightens the system even further. Fear of shortage begets the shortage. It becomes a vicious circle.”

Indeed, long gas lines were reported throughout the U.S. following Katrina [26], which temporarily crippled the nation’s drilling and refining capacity.

Note that we are not arguing that gasoline *consumption* increased following the hurricanes; presumably, nationwide consumption remained relatively steady. Rather, the supply shock changed the *variability* of gasoline purchases, since a sudden increase in fuel purchases would be followed by a subsequent decrease if overall consumption is constant. In this case, customers reacted to the sudden drop in supply capacity, skewing their demand pattern. This explains why the RBWE, rather than the BWE, may occur during times of reduced capacity, especially if the capacity changes are random.

## 1.2 The Bullwhip Metaphor

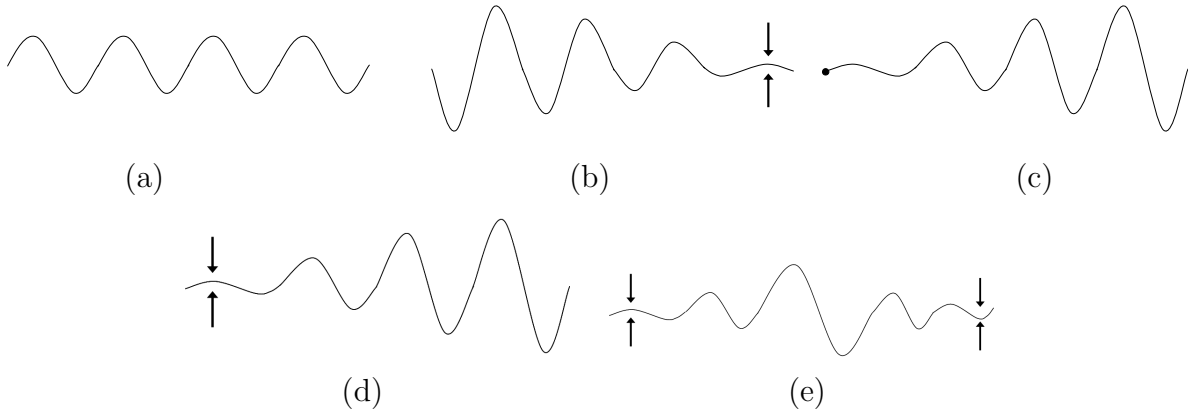
To illustrate the RBWE, we extend the common metaphor of the supply chain as a string or whip, with the left-hand side representing upstream supply and the right-hand side representing downstream demand. Demand variability is represented as a vibration applied to the right end of the string. It is well known that a base-stock policy is optimal at each stage of a serial supply chain (and thus the BWE does not occur) if demands and purchase prices are stationary, upstream supply is infinite with a fixed lead time, and there is no fixed order cost [23]. In this case, demand vibrations are transmitted without modification up the string, as in Figure 1(a). It has been argued [36] that demand spikes act as shocks applied to the right end of the string, and that these shocks amplify as they move up the string, causing the BWE (Figure 1(b)).

If, instead, the left end of the string acts as a “fixed point” (that is, it is immovable), then vibrations will tend to dampen (rather than amplify) as they move up the string (Figure 1(c)). Such a fixed point may represent an upstream supply shortage: The upstream stage utilizes 100% of its (now reduced) capacity, so it has no variability in its order quantities. The vibration (demand) amplitude can only increase as one moves downstream—the RBWE.

Alternately, we can think of the RBWE a magnification of a wave (Figure 1(d)) that initiates upstream and propagates downstream (rather than as the dampening of a wave that propagates upstream). In this type of RBWE, a shock (in the form of a random capacity change) is applied to the upstream portion of the bullwhip, and the wave amplitude increases as it propagates downstream. We discuss both types of RBWE in this paper.

Moreover, when an exogenous demand shock with fixed vibration coexists with a tight capacity due to a sudden supply disruption, the order volatility may be smallest at the

Figure 1: String vibrations (a) with no amplification, (b) with a demand vibration and BWE, (c) with a demand vibration, a fixed point, and RBWE, (d) with a supply shock and RBWE, and (e) with both RBWE and BWE.



ends of the supply chain and largest in the middle (Figure 1(e)). We call this an “umbrella pattern” because a plot of order variability stage by stage resembles an umbrella shape. In this case, the shock generated by one end is amplified at the beginning but dampened due to the fixed point at the other end, vice versa. This pattern occurs frequently in our beer game experiment and simulation study.

### 1.3 Experiment Overview

In order to verify the existence of RBWE, we use a variant of the beer game to test people’s behaviors in a serial supply chain subject to random capacity shocks, i.e., random decreases in capacity. (Previous beer game experiments have assumed uncertainty at the demand side only, except the supply uncertainty that results from stockouts at each stage.) We find that a significant portion of players’ ordering patterns exhibit RBWE. However, one recurring question with any beer game experiment is whether the participants are sufficiently representative of purchasing managers in actual supply chains. This question arises for two reasons. First, the majority of participants in published beer game studies are students rather than managers. Second, the level of trust among the participants plays an essential role in the experiment’s outcome. If the participants do not know each other or are assigned to roles and teams randomly, as is common in published experiments, it is unlikely that players will trust each other to make competent decisions. In fact, Croson et al. [14] report that this lack of trust can cause the BWE even when the demand is constant and known to all players. However, zero trust rarely occurs among suppliers and buyers in the real world,

especially after months or years of repeated cooperation.

Despite these limitations, beer game experiments still provide valuable information. For example, they are useful for revealing the underlying order decision rules followed by the players, which can then be quantified using regression analysis based on the data collected in the experiments. However, players' behaviors can be quite different from one another. Each player tends to emphasize different components in his or her decision rule, and with different magnitudes, making it difficult to assess the prevalence of the RBWE from beer game experiments alone. Therefore, we couple our beer game experiment with a simulation study to examine the impact of a wide range of ordering behaviors on the supply chain as a whole. Whereas our beer game experiments provide a description of the behaviors of a particular set of players, our simulation studies postulate a wider range of behaviors and determine the resulting effect on the pattern of order volatility in the supply chain.

Using our beer game and simulation experiments, we explore the behavioral causes of the BWE and RBWE. Previous beer game studies (e.g., [13, 36]) have suggested that the BWE is caused by demand uncertainty and an underweighting of the supply line. Our results confirm these findings. We also find the inverse result: that overreaction to supply disruptions and overweighting of the supply line can cause the RBWE. Using the terminology of our bullwhip metaphor in Section 1.2, overreaction to supply shocks serves as an amplifying factor, overweighting of the supply line serves as a dampening factor, and both cause the RBWE.

The remainder of the paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we explain the basic settings for our experiments and propose several order functions to model players' ordering behavior. Sections 4 and 5 discuss the results of our beer game and simulation experiments, respectively. Finally, we summarize our conclusions in Section 6.

## 2. Literature Review

Most supply chain management research tries to answer the question of what managers *should* do. In contrast, a recent focus on behavioral studies in operation management provides insight into what managers *would* do under various settings. Such research not only validates established theories but also encourages the development of new ones. Most behavioral studies of the BWE are carried out through the beer game. Sterman [36] introduces the

game and observes order amplification due to the underweighting of the supply line—that is, players tend to ignore some or all of their pipeline inventory and instead base their ordering decisions primarily on their on-hand inventory.

The behavioral study by Sterman [36] and the theoretical results developed by Lee, et al. [23] have stimulated numerous theoretical studies on the causes of the BWE (see the survey by Lee, et al. [22]), as well as a number of additional beer game experiments that attempt to reconcile the theories with actual human behavior, as well as to explore other behavioral causes of the BWE.

Kaminsky and Simchi-Levi [19] find that a reduction in order information delay and shipment leadtime results in lower total supply chain costs but not in a reduction of order variability amplification. Chen and Samroengraja [9] make the mean and standard deviation of the normally distributed demand known to every player and find that, though the four operational causes are removed, the BWE still occurs. Croson and Donohue [12] observe a decrease in the magnitude of the BWE in the point-of-sale (POS) treatment group, who know the realized customer demand, when compared with the control group, who know only the underlying demand distribution. The primary reason for the decrease is that the participants in the POS treatment group almost equally utilize the realized customer demand and the order information from their immediate downstream stage in their ordering decisions. Steckel et al. [35] show that POS information can actually increase a team’s costs when it distracts the participants under certain types of customer demand.

Croson and Donohue [13] tell the participants the status of the inventory across the supply chain at any point in time. The magnitude of the BWE decreases compared with the situation in which participants are not provided with such information, because upstream stages use downstream inventory information to anticipate and adjust their orders. Oliva and Gonçalves [28] suggest that participants respond differently to their own on-hand inventory and backorders due to the difference between holding and backorder costs and find that participants tend to ignore their own backorders rather than over-reacting to them and placing panicked orders. Wu and Katok [41] show that effective communication along with learning can significantly diminish the magnitude of BWE. Croson et al. [14] show that the BWE still persists even if the demand is constant and known to every player. They attribute this to “coordination risk”; that is, players place larger than necessary orders to protect themselves against the risk that other players will not behave optimally.

Despite its potential to systematically investigate the outcomes generated by various

ordering behaviors, simulation has rarely been used in the BWE literature. An exception is Chatfield, et al. [8], who use simulation to study the effect of players' behaviors in a beer game in which all stages are managed by computer, rather than by live players. Their order functions are very similar to the base stock policy studied by Chen, et al. [10]. Chatfield, et al. find that an increase in the variance of the stochastic lead time results in greater BWE, while information sharing dampens BWE. Furthermore, they provide three forecast models under stochastic lead times. The model that forecasts demand and leadtime separately leads to higher forecast variability and therefore higher order variability than the other two, one ignoring leadtime uncertainty and the other forecasting leadtime demand. The BWE reaches its maximum magnitude when demand and leadtime are estimated separately.

Another area of behavioral studies in supply chain management is the newsboy problem. Behavioral studies of the newsboy problem can provide valuable insight into managers' actions under more complex coordination mechanisms and other settings, since the newsboy problem is one of the most important building blocks of supply chain management. Schweitzer and Cachon [32] study players' responses to high-profit and low-profit products in the newsboy setting and find that orders are close to the demand mean regardless of the product type. This behavior can be explained by the anchoring and adjustment method [40], in which participants treat the mean demand as a starting point and make adjustments toward optimal solution. Bolton and Katok [6] demonstrate that participants in a newsboy game tend to make decisions based on only partial data of the realized demand, and that the flat newsboy profit curve prevents participants from approaching the optimal order quantity quickly. Keser and Paleologo [20] extend the newsboy problem to the wholesale price contract and find that participants are willing to split the profit roughly equally between them, despite the ability of one player to take the majority of the profit.

Readers interested in behavioral studies in other aspects of operations management are referred to the survey by Bendoly et al. [4], who categorize such studies into three groups based on the assumptions used—intentions, actions, and reactions. Using this categorization, they review all of the behavioral papers that were published in six journals from 1985 to 2005. Gino and Pisano [15] provide a review of behavioral studies in operation management within a broader time frame and compare it with the progress of behavioral studies in other fields, such as economics, marketing, and finance.

Current studies on supply disruptions are based on the assumption of the rationality of decision makers. Parlar and Berkin [29], Berk and Arreola-Risa [5], Parlar and Perry [30, 31],

Gupta [17], Mohebbi [24], and many others modify classical inventory models to cope with supply disruptions. Tomlin [38] examines how the optimal mitigation strategy (backup inventory, supplier redundancy, or some combination) changes as the characteristics of the disruptions change. Tomlin and Snyder [39] take into consideration the benefit of advance warning of supply disruptions. Babich et al. [2] study the impact of supplier default risk on the relationship between one retailer and multiple suppliers. Kim, et al. [21], Hopp and Yin [18], and Snyder and Shen [34] extend the study of supply disruptions to multi-echelon supply chains.

Since managers have limited experience in dealing with supply disruptions due to their low probability of occurrence, it may be difficult to apply the models cited in the previous paragraph in practice. Moreover, just as Thietart and Forgues [37] suggest that the “butterfly effect” (that is, a small variation at one point may cause a large variation of the whole system) can exist in organizations, so, too, can a small disruption be amplified by irrational decision makers within a supply chain. Therefore, studying human behaviors under disruptions is important. One of the major contributions of our paper is to examine people’s behavior when they face supply disruptions, and its impact on order-variability propagation in a multi-echelon setting.

### 3. Basic Settings and Order Decision Rules

In our beer game experiment and simulation, we study a 4-stage serial supply chain under periodic review. Stages 1–4 correspond to the retailer, wholesaler, distributor, and manufacturer, respectively. The retailer receives demand from an external customer. The demand is fixed to 50 units per period. (The exception is Section 5.1, in which we simulate and examine the impact of the weight of inventory level and supply line under demand uncertainty only.) The manufacturer has a production capacity that limits the quantity it may order in a given period; see Section 3.1.

In each period, each stage  $i$  experiences the following sequence of events:

1. The shipment from stage  $i + 1$  shipped two periods ago arrives at stage  $i$  (that is, the leadtime is 2). If  $i = 4$ , stage  $i + 1$  refers to the external supplier.
2. The order placed by stage  $i - 1$  in the current period arrives at stage  $i$ . If  $i = 1$ , stage  $i - 1$  refers to the external customer.

3. Stage  $i$  determines its order quantity and places its order to stage  $i + 1$ .
4. The order from stage  $i - 1$  is satisfied using the current on-hand inventory, and excess demands are backordered. Holding and/or stockout costs are incurred.

To reflect the modern data-processing environment (e.g. EDI) and to maintain consistency with our assumption that information about disruptions is propagated instantaneously, we assume (unlike Sterman [36] and subsequent papers) no order information delay, i.e., stage  $i$  receives order information in the same period that the order is placed by stage  $i - 1$ .

### 3.1 State Variables

We introduce the following random variables that describe the state of the system in any period:

- $IL_t^i$ : Inventory level (on-hand inventory – backorders) at stage  $i$  after event 2 (i.e., after observing its demand but before placing its order) in period  $t$ .
- $IP_t^i$ : Inventory position (on-hand inventory + on-order inventory – backorders) at stage  $i$  after event 2 in period  $t$ .
- $O_t^i$ : Order quantity placed by stage  $i$  in event 3 in period  $t$ . If  $i = 0$ ,  $O_t^i$  represents demand from the external customer.
- $\hat{O}_t^i$ : Forecast of order quantity that will be placed by stage  $i$  in period  $t$ . This forecast is calculated by stage  $i + 1$  after event 2 in period  $t - 1$ . (See Section 3.2.3.)
- $\xi_t$ : Production capacity at stage 4, i.e., the maximum quantity that stage 4 can order, in period  $t$ .
- $\sigma_i$ : Standard deviation (SD) of orders placed by stage  $i$  across the time horizon.

Note that the order quantity  $O_t^i$  is listed as a random variable, rather than as a decision variable, because order quantities are treated as a function of other random variables (see Section 3.2) and, in the case of the beer game, may be subject to additional, human, randomness.

The production capacity at stage 4,  $\xi_t$ , is also a random variable. We divide periods into two groups, labeled “up” and “down”.  $\xi_t$  is larger than the demand observed by the

retailer during up periods and smaller during down periods. This setting is consistent with the supply disruption literature cited in Section 2. The difference is most papers set  $\xi_t = 0$  during down periods, but we set  $\xi_t > 0$  to model the situation in which capacity is reduced but not totally eliminated during a disruption. See Section 4.1 for more details on the supply process  $\xi_t$ .

## 3.2 Order Quantity Functions

We introduce two order quantity functions that express the order quantity as a function of several state variables. The *base order function* comes directly from Sterman [36]. The *disruption order function* allows players to behave differently based on whether the capacity is in its normal or disrupted (up or down) state.

In our simulation studies, these functions are used to determine the order quantity placed by each stage in each period. In our beer game experiment, we calibrate players' observed behaviors to these functions to determine which state variables players consider when choosing an order quantity, and to what extent. This analysis is motivated by that of Sterman [36].

### 3.2.1 Base Order Function

Our base order function is identical to the function proposed by Sterman [36]:

$$O_t^i = \max\{0, \hat{O}_{t+1}^{i-1} + \alpha_b^i(IL_t^i - a_b^i) + \beta_b^i(IP_t^i - IL_t^i - b_b^i)\}, \quad (1)$$

where  $a_b$  and  $b_b$  represent target values for the inventory level ( $IL$ ) and supply-line inventory ( $IP - IL$ ), respectively. The constants  $\alpha_b$  and  $\beta_b$  are adjustment parameters controlling the change in order quantity when the actual inventory level and the supply line, respectively, deviate from the desired targets. (The subscript  $b$  stands for “base”.) Sterman based this order function on the anchoring and adjustment method proposed by Tversky and Kahneman [40]. It accounts for changes in the demand, inventory level, and supply line dynamically, even when the demand and supply processes are unknown.  $\hat{O}_{t+1}^{i-1}$  is treated as the anchor, serving as a starting point for the order quantity, while the remaining part is the adjustment to correct the initial decision based on the inventory level and supply line. The relationship between  $|\alpha_b|$  and  $|\beta_b|$  determines how the supply line is weighted:  $|\alpha_b| > |\beta_b|$ ,  $|\alpha_b| = |\beta_b|$ ,  $|\alpha_b| < |\beta_b|$  results in underweighting, equal weighting, and overweighting the supply line, respectively.

The order quantity placed by stage 4 in period  $t$  is bounded by its capacity  $\xi_t$  in that period. Therefore the actual order placed by stage 4 in period  $t$  is  $\min\{O_t^4, \xi_t\}$ .

### 3.2.2 Disruption Order Function

In reality, a huge supply disruption is usually known publicly. This information about capacity shocks may have an impact on buyers' behavior, e.g., by increasing purchase quantities. In order to examine whether players behave differently with or without supply disruptions, we propose the “disruption order function”:

$$O_t^i = \max\{0, \hat{O}_{t+1}^{i-1} + \alpha_d^i(IL_t^i - a_d^i) + \beta_d^i(IP_t^i - IL_t^i - b_d^i) + \gamma_d^i S_t\}, \quad (2)$$

where  $S_t$  is a public signal to indicate whether there is a supply disruption in the system.  $S_t = 1$  if stage 4 is in the down state and 0 otherwise. (The subscript  $d$  stands for “disruption.”) If  $\gamma_d^i < 0$ , then the stage is willing to order less during a disruption in order to reduce potential backorders at its supplier. If  $\gamma_d^i = 0$ , the stage ignores disruptions, while if  $\gamma_d^i > 0$ , then the stage orders more during a disruption to protect against further decreases in capacity.

As in the base order function, the actual order quantity placed by stage 4 is given by  $\min\{O_t^4, \xi_t\}$ .

### 3.2.3 Demand Forecast

In both order functions,  $\hat{O}_{t+1}^{i-1}$  is a forecast of demand that will be observed by stage  $i$  in period  $t + 1$ . It is calculated using exponential smoothing:

$$\hat{O}_{t+1}^{i-1} = \eta O_t^{i-1} + (1 - \eta)\hat{O}_t^{i-1}, \quad (3)$$

where  $\eta$  is the smoothing factor,  $0 \leq \eta \leq 1$ .

## 3.3 Interpretation of Order Standard Deviation

We examine the presence of the BWE or RBWE at each stage individually. When  $\sigma_i > \sigma_{i-1}$ , stage  $i$  amplifies its order variability; i.e., the bullwhip effect (BWE) occurs at stage  $i$ . If  $\sigma_i < \sigma_{i-1}$ , then the reverse bullwhip effect (RBWE) occurs at stage  $i$  instead.

If  $\sigma_{i+1} > \sigma_i$  for all  $i \leq 3$ , then the system exhibits pure BWE, and when  $\sigma_{i+1} < \sigma_i$  for all  $i \leq 3$ , the system exhibits pure RBWE. There are also several other possible shapes for the pattern of order standard deviations across the supply chain. For example, when  $\sigma_{i+1} > \sigma_i$  for  $i = 1, 2$  and  $\sigma_{i+1} < \sigma_i$  for  $i = 3$ , the order pattern resembles an umbrella; this pattern

is natural when the downstream part of the supply chain is affected primarily by demand uncertainty while the upstream is bounded by the capacity process.

## 4. Beer Game Experiment

Our beer game setup is motivated in part by consumer buying patterns for gasoline following hurricane Katrina. Katrina disabled approximately 10% of U.S. oil refining capability, as well as a substantial portion of its drilling facilities [25], creating a sudden and severe shock to the upstream stages of the gasoline supply chain. Customers were aware of this shock (but not of the magnitude of its downstream effect), and many of them filled their cars at the beginning of the shock in order to avoid future shortage and price fluctuations. Although the impact of price fluctuations is not tested in the beer game, we can still test players' response to possible shortages created by the supply uncertainty.

In our beer game experiment, we create capacity shocks during the game to observe how players behave during supply disruptions. All players know when a capacity shock is occurring, but only the player in the role of the manufacturer knows its severity. We describe our experimental design in Section 4.1 and the results of the beer game experiment in Section 4.2.

### 4.1 Experimental Design

Our beer game experiment was conducted using an Excel-based implementation written by the authors. Our computerized implementation gives players more information about the status of the system than in the traditional board version of the game. Figure 2 shows the game's user interface. Players can easily acquire information about their own on-hand inventory, backorders, on-order inventory, and in-transit inventory, as well as backorders at their supplier.

Each player is randomly assigned to a team and role. No communication is allowed during the game. Our implementation automates the information-transfer process: when a player places an order, it is transmitted electronically to his or her upstream neighbor, and when orders are shipped, the delivery quantity is transmitted downstream electronically. This reduces transaction errors and speeds the playing of the game.

Following Sterman [36], we set the holding and backorder cost to \$.5 and \$1, respectively, at every stage of the supply chain. In order to focus the study on the supply uncertainty



Figure 2: Screenshot of Beer Game

faced by the whole supply chain, we fix demand to 50 units per week and make it known to every player to remove demand uncertainty from the whole system.

The manufacturer has a capacity limitation on his or her order size. The capacity fluctuates throughout the game, following a two-state discrete-time Markov process. The “up” state corresponds to full capacity  $\xi_u$  and the “down” state corresponds to disrupted capacity  $\xi_d$ . We fix  $\xi_u = 60$  and allow  $\xi_d$  to vary randomly at each disruption according to a normal distribution with mean 40 and variance 4. The transition probability from the up state to the down state is  $p_d$ , and that from the down state to the up state is  $p_u$ . The stationary probabilities of being in the up and down states are therefore  $p_u/(p_d + p_u)$  and  $p_d/(p_d + p_u)$ , respectively. To ensure the stability of the system, we require  $(\xi_u p_u + E(\xi_d) p_d)/(p_d + p_u) > 50$ . In the experiment, we set  $p_d = 0.2$  and  $p_u = 0.3$ . Hence our average capacity is 52.

The players were informed of the shape of disruption distribution, but the actual values of the distribution parameters  $(p_u, p_d, \xi_u, \xi_d)$  were unknown to them. Each trial used the same sample path, which was generated randomly at the outset and then repeated to ensure that fair comparisons could be made from trial to trial. This sample path includes 17 down periods in the first 50 periods. The players were notified (via an indicator in the beer game screen) whether a disruption is in progress, but they did not know how severe the disruption was. The exception is the manufacturer, who can determine the capacity in any period since

the program prompts him or her for a new order quantity if the quantity entered exceeds the capacity.

Our experiment consisted of 32 participants (eight teams of four) from Lehigh University, including 8 graduate students and 24 undergraduate students. Roughly half of the participants received a cash incentive for playing the game (the other half was required to play as part of a course they were enrolled in). For those receiving cash, the amount of the award was scaled based on the teams' performance in a manner similar to that described by Croson and Donohue [12]. Each trial lasts up to 1 hour and 45 minutes. The introduction lasts 20 minutes, followed by a roughly 10-minute practice round in which the participants play for 5 periods to familiarize themselves with the software environment. The remaining time is used for the actual experiment. The maximum number of periods per trial is 50; most teams were able to finish at least 40 periods, though one team played for only 31 periods.

One of the eight teams (team 6) exhibited a mean order quantity at the retailer and the wholesaler of 77.4 and 91.2, respectively, both of which are more than two standard deviations above the mean order quantity for all retailers and wholesalers (and significantly above the demand of 50 per period). Therefore, team 6 has been omitted from the results below as an outlier.

## 4.2 Beer Game Results

We find that less than half of the players in our beer game experiment exhibited BWE during supply disruptions. After further exploration, we find that disruptions lead to the decrease of order by the downstream players. Depending on whether upstream players underweight or overweight supply line in the face of the demand shock created by their downstream partners, they exhibit BWE or RBWE (respectively).

Section 4.2.1 provides an analysis of the existence of the BWE and RBWE. In Section 4.2.2, we examine the relationship between BWE/RBWE and the weighting of the supply line. Additionally, the impact of people's reaction to supply disruptions on BWE/RBWE is discussed in Section 4.2.3.

### 4.2.1 The Existence of BWE and RBWE

One of the major purposes of our version of the beer game is to test the prevalence of the BWE under an environment different from the standard beer game setup. Our results suggest that the BWE no longer dominates when supply disruptions are present. Prior to

Table 1: SD of orders for each role.

Team	All Periods				Down Periods Only			
	R	W	D	M	R	W	D	M
1	0.00	41.76	13.34	15.35	0.00	29.17	16.12	11.10
2	11.22	24.99	14.55	10.25	9.81	28.54	9.76	2.07
3	7.57	21.58	14.38	13.40	7.55	33.27	19.84	6.58
4	4.71	6.99	9.48	9.97	7.38	5.56	8.77	3.11
5	13.02	13.08	19.62	14.49	11.98	11.21	21.65	8.22
7	26.74	14.70	21.85	16.50	23.56	13.36	12.14	5.81
8	11.47	7.56	5.62	9.66	12.95	7.16	5.74	4.79
Mean	10.67	18.67	14.12	12.80	10.46	18.32	13.43	5.95

performing our experiment, we conjectured that the RBWE would occur more often than the BWE *during down periods*, but that the BWE may dominate when the SD is calculated over all periods. This reflects the suggestion that supply disruptions cause RBWE and the fact that, taken across all periods, the upstream stage’s order process is actually more volatile because the capacity changes themselves cause order variance.

Table 1 contains the SD of the players’ orders for all teams (except team 6, which is omitted as described in Section 4.1). Standard deviations are reported both across all the periods and for down periods only. The column labels R, W, D, and M represent retailer, wholesaler, distributor, and manufacturer, respectively.

Table 1 indicates that 57.1% of players exhibited RBWE during down periods, confirming our conjecture that the RBWE occurs during disruptions. Even when taken across all periods, 35.7% of players exhibited RBWE.

The RBWE can occur at wholesalers, distributors and manufacturers, both during down periods and across all periods. Figure 3 provides a graphical representation of the order SD of each team during down periods. The thicker line represents the mean of the order standard deviation over all 7 teams, while the thinner lines represent each individual team. The general trend in Figure 3 is an “umbrella” shape, with demand variability increasing (BWE) downstream but decreasing (RBWE) upstream. Except for the retailer, the “average” player in each role exhibits RBWE.

To test whether the differences in SD between orders and demands (i.e., the differences among the numbers in Table 1) are statistically significant, we consider the following null hypothesis:

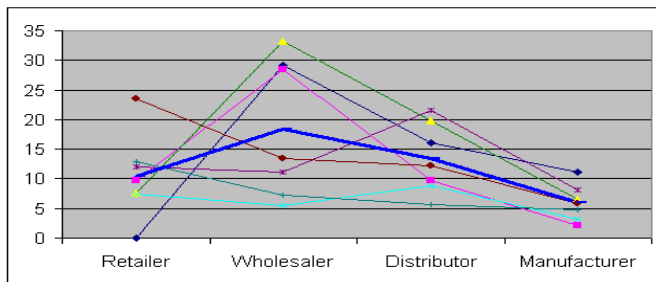


Figure 3: SD of orders during supply disruptions. (Thinner lines represent individual teams; thicker lines represent mean.)

Table 2: Results of Spearman’s rank correlation test for Hypothesis 1

Team	All Periods				Down Pers Only			
	R	W	D	M	R	W	D	M
1	0	1	-1	1	0	1	0	-1
2	1	1	-1	0	1	1	-1	-1
3	1	1	-1	0	1	1	-1	-1
4	1	1	1	0	1	0	1	-1
5	1	0	1	0	1	0	1	-1
7	1	-1	1	0	1	-1	0	-1
8	1	-1	-1	1	1	-1	0	0
BWE	6	4	3	2	6	3	2	0
None	1	1	0	5	1	2	3	1
RBWE	0	2	4	0	0	2	2	6

**Hypothesis 1** *There is no amplification of either order or demand variability. That is, the order SD is equal to the demand SD.*

Since each player’s orders and demands are dependent, and their distributions are unknown, a standard  $F$ -test cannot be performed. Instead, we transform Hypothesis 1 to test instead whether the correlation of coefficients of  $O^i - O^{i-1}$  and  $O^i + O^{i-1}$  is zero.

To test this correlation, we applied Spearman’s rank correlation test using a level of significance of 0.1. The results are shown in Table 2, in which 0 indicates that the player does not show a significant difference between order and demand SDs (no BWE or RBWE), 1 indicates that the order SD is statistically larger than the demand SD (BWE), and  $-1$  indicates the reverse (RBWE). The final three rows indicate the number of players exhibiting each type of behavior.

Table 2 indicates that, during down periods, 10 out of 28 players (35.7%) exhibit RBWE

and 11 out of 28 (39.3%) exhibit BWE. When taken across all periods, 6 out of 28 players (21.4%) exhibit RBWE, while 15 out of 28 (53.6%) exhibit BWE.

All but one of the manufacturers exhibit strong RBWE during down periods because their orders are bounded by the reduced capacity. On the other hand, no manufacturers exhibit RBWE when taken across all periods, since the capacity changes necessarily cause order variability on the part of the manufacturer. The retailers automatically exhibit strong BWE because they face no demand uncertainty, so any variability in their orders creates BWE. Taken together, these results confirm our conjecture that during disruptions, BWE occurs downstream and RBWE upstream.

There is no clear pattern to whether BWE or RBWE dominates at wholesalers and distributors during supply disruptions: There are 5, 5, and 4 players as either the wholesaler or distributor exhibiting BWE, no BWE, and RBWE, respectively. In the next two subsections, we explore the question of why some wholesalers and distributors exhibit BWE, some exhibit RBWE, and some exhibit neither.

The remainder of this analyzes BWE and RBWE during disrupted periods only.

#### 4.2.2 BWE/RBWE and Supply Line Weighting

Sterman [36] suggests that one of the main causes of the BWE is that people tend to weight the supply line less than the inventory level when choosing an order quantity. But when the system faces supply uncertainty rather than demand uncertainty, does players' behavior change?

To answer this question, we first estimate the parameters of the base order function (see Section 3.2.1) for each individual player, except for the manufacturers since their orders are bounded by the capacity. A simple least-squares fit cannot be applied in this case, because such a procedure would have infinitely many optimal values for the targets  $IL(a_b^i)$  and  $IP-IL(b_b^i)$ . This is because only  $\alpha_b^i$ ,  $\beta_b^i$  and  $\alpha_b^i a_b^i + \beta_b^i b_b^i$  can be predicted. Therefore, we follow the statistical procedure used in previous beer game studies (e.g., [12, 13, 28]) to calibrate the order quantity function to observed data by treating  $-\alpha_b^i a_b - \beta_b^i b_b$  as a single constant. Since all players know that the external customer demand is fixed to 50, demand forecasting is not required, so we set the smoothing factor  $\eta = 0$ .

The results of the regression are shown in the first set of columns in Table 3. (The second set of columns will be used in Section 4.2.3.) The columns labeled  $\hat{\alpha}_b$  and  $\hat{\beta}_b$  give the parameter estimates. The column labeled Weighting Type indicates the supply-line

Table 3: Regression results for base and disruption order functions

	Base			Disruption			
	$\hat{\alpha}_b$	$\hat{\beta}_b$	Weighting Type	$\hat{\alpha}_d$	$\hat{\beta}_d$	$\hat{\gamma}_d$	Reaction Type
R1	NA	NA	NA	NA	NA	NA	NA
W1	-0.19	-0.44	-1	-0.19	-0.41	-47.24	-1
D1	-0.13	-0.01	1	-0.12	-0.01	-0.48	-1
R2	-0.19	0.07	1	-0.19	0.06	-1.13	-1
W2	-0.43	-0.01	1	-0.43	-0.02	0.76	1
D2	-0.07	-0.10	-1	-0.07	-0.10	3.22	1
R3	-0.66	-0.55	1	-0.65	-0.54	-4.36	-1
W3	-0.15	-0.23	-1	-0.17	-0.26	10.94	1
D3	-0.47	-0.64	-1	-0.48	-0.65	-5.29	-1
R4	-0.50	-0.12	1	-0.51	-0.12	-0.87	-1
W4	-0.57	-0.41	1	-0.57	-0.41	-3.41	-1
D4	-0.48	-0.14	1	-0.47	-0.14	-2.39	-1
R5	-0.12	-0.06	1	-0.14	-0.07	-9.77	-1
W5	-0.04	-0.07	-1	-0.04	-0.08	0.71	1
D5	-0.37	0.08	1	-0.37	0.08	-4.04	-1
R7	0.02	-0.04	-1	0.02	-0.03	-21.72	-1
W7	-0.11	0.15	-1	-0.10	0.17	-6.57	-1
D7	-0.31	-0.16	1	-0.32	-0.17	-15.95	-1
R8	-0.10	-0.10	-1	-0.10	-0.09	-11.57	-1
W8	0.02	-0.19	-1	0.02	-0.14	-3.32	-1
D8	-0.14	-0.13	1	-0.09	-0.09	-5.43	-1
Mean	-0.25	-0.16		-0.25	-0.15	-6.39	

Table 4: Results of hypothesis test for equal weight of inventory level and supply line

Team	R	W	D
1	NA	-1*	1
2	1	1*	0**
3	1	0*	-1**
4	1	1	1*
5	0	0	1*
7	0	0**	0
8	0	-1**	0

Note: \* and \*\* indicate that the player exhibits BWE or RBWE, respectively.

weighting for each player: 1 represents underweighting, while  $-1$  indicates overweighting. Note that regression is not applicable for one player, R1, who ordered exactly 50 units every week.

Our main focus is the behavior of wholesaler and distributor. In Table 2, only 7 out of 14 wholesalers and distributors underweight the supply line, while another 7 overweighting it. This result is significantly different from that of Croson and Donohue [12, 13], who find that 98% of 172 players underweight the supply line. To test the statistical significance of this observation, we formulate Hypothesis 2:

**Hypothesis 2** *Wholesalers and distributors treat the inventory level the same as the supply line. That is  $\alpha_b = \beta_b$ .*

Table 4 shows the  $F$ -test results for Hypothesis 2 using a 0.1 level of significance. The results for retailers are included for comparison. In the table, 1 indicates whether the weight placed on the inventory level is significantly higher than that placed on the supply line (underweighting), while  $-1$  indicates overweighting. A 0 indicates that there is no significant difference in weight between the inventory level and the supply line. An asterisk (\*) indicates that the player exhibits a statistically significant degree of BWE in Table 2, while a double-asterisk (\*\*) indicates RBWE.

We reject Hypothesis 2 for 8 out of 14 wholesalers and distributors. Of these 8, 5 underweight the supply line and 3 overweight it. The results suggest that overweighting may be one of the major reasons for the RBWE. In particular, of the 4 wholesalers and distributors exhibiting RBWE during disruptions, none underweights supply line. Of the 5 wholesalers and distributors exhibiting BWE, only one of them overweighted supply line.

Conversely, of the 5 wholesalers and distributors players underweighting the supply line, none exhibits RBWE and 3 exhibit BWE. Similarly, 2 of the 3 wholesalers and distributors overweighting the supply line exhibit RBWE. We can see that underweighting supply line is still a major reason to cause the BWE even if supply uncertainty is introduced to the system. On the other hand, the presence of supply disruptions causes people to think more about the supply line, hence overweighting it; those who do are more likely to exhibit the RBWE.

### 4.2.3 BWE/RBWE and Reaction to Supply Disruptions

The base order function doesn't capture the difference in people's behavior during up and down periods. To evaluate this difference, we estimated the parameters for the disruption order function using the same statistical procedure as in Section 4.2.2, except that we use the disruption order function in place of the base order function. The results are displayed in the second set of columns in Table 3. The column labeled Reaction Type contains 1 if the player increases his or her order size during disruptions ( $\gamma_d > 0$ ) and  $-1$  if the player decreases his or her order size ( $\gamma_d < 0$ ).

In Table 3, only 4 out of 20 players have  $\gamma_d > 0$ , and all the other players have  $\gamma_d < 0$ . This result suggests that players are very likely to decrease their intended order size during supply disruptions to prevent backorders at their suppliers. We believe this is because the beer game is centralized, and players are evaluated based on the performance of the whole team. This setting is different from the hurricane Katrina example, in which customers act in their own best interests.

To test whether people behave significantly different as a response to a capacity shock, we use the following null hypothesis:

**Hypothesis 3** *Players ignore the supply disruption signal. That is,  $\gamma_d = 0$ , and the disruption order function degenerates to the base order function.*

The results, using a level of significance of 0.1, are shown in Table 5. In this table, 0 indicates a player who does not behave statistically differently during up and down periods, while 1 [ $-1$ ] means that during disruptions the player orders significantly more [less] than they do in normal periods.

Table 5 indicates that no player orders significantly more during disruptions than during normal periods. For 6 out of 7 teams, the downstream stages (retailer or wholesaler) order

Table 5: Results of hypothesis test for reaction to disruptions

Team	R	W	D
1	NA	-1*	0
2	0	0*	0**
3	-1	0*	0**
4	0	-1	0*
5	-1	0	0*
7	-1	0**	-1
8	-1	0**	-1

Note: \* and \*\* indicate that the player exhibits BWE or RBWE, respectively.

significantly less during disruptions, which indicates that players downstream tend to react to disruptions. This creates a (negative) demand shock for their upstream partners, who will underweight or overweight the supply line depending on whether they pay more attention to their customer or supplier. As a result, both the type of reaction to disruptions and the supply-line weighting type affect whether the upstream stages exhibit BWE or RBWE.

## 5. Simulation Study

Although the beer game can provide valuable insights into players' individual behaviors, it can be difficult to draw general inferences from such an experiment for two reasons. First, the total cost of the supply chain is highly dependent on the behavior of the individuals in the chain, rather than on general behavior. It is the individual behaviors and the arrangement of players in a team that matter. Second, from previous studies [13, 36], we know that individuals behave quite differently from each other, and the behaviors of the participants in a given team may interact strongly. The same player, if assigned to different groups, may even behave differently due to the effect of other players.

Another drawback of the beer game experiment is the time limit. To achieve some sort of stable behavior, the participants need to learn the order patterns of their customer and supplier, and this may take a long time. This suggests that the estimated parameters in the order function vary over time at the beginning of the horizon. However, the time limitation prevents the beer game from being played long enough to achieve stability.

In addition, there are differences between the incentives in the beer game and in a real business setting. In the beer game, the total cost of the supply chain is the performance measure, while real businesses care about their own profit, not (directly) that of their partners.

This may cause different values of the parameters in the order function, e.g., the customers in the hurricane Katrina example may have positive  $\gamma_d$  instead of negative ones.

Finally, due to time and cost considerations, it is possible to test only a limited set of assumptions in the beer game (e.g., one type of disruption process, etc.).

These drawbacks can be addressed using a simulation study, in which all stages are operated by computer rather than by humans, following pre-defined ordering rules. Such a study makes it convenient to perform what-if analysis regarding different ordering behaviors, disruption processes, and so on. It is also trivial to run the system long enough to achieve an approximately steady state. Thus, our simulation study complements our beer game experiment and may be viewed as serving a sensitivity analysis role.

To perform our study, we used the freeware software called BaseStockSim developed by Snyder [33], which simulates multi-echelon supply chains with stochastic supply and demand. Each stage can have its own ordering function, following any of several types of inventory policies, including base stock,  $(r, Q)$ ,  $(s, S)$ , and various anchoring and adjustment order functions.

Our goal is to simulate the system with different parameter values to determine the impact of various behaviors on ordering patterns across the whole system. For each setting of the parameters, we simulated the system for 10 trials, each consisting of 1000 periods with a 100-period warm-up interval.

In Section 5.1, we establish the relationship between BWE/RBWE and supply-line weighting type under demand uncertainty only in order to validate our model against previous studies. Then, in section 5.2, we investigate the impact of supply-line weighting type and disruption reaction on BWE/RBWE. Finally, in Section 5.3, we consider the impact of different capacity processes on BWE/RBWE.

## **5.1 Effect of Supply-Line Weighting under Demand Uncertainty Only**

Previous experimental studies, such as Sterman [36], show through regression analysis that underweighting the supply line is the major factor in causing BWE. To evaluate the relationship between BWE/RBWE and supply-line weighting type, as well as its magnitude under demand uncertainty only, we use a 2-stage model consisting of a retailer and a wholesaler. The demand follows a normal distribution with mean 50 and standard deviation 10. There is no capacity limitation at the wholesaler. The exponential smoothing factor  $\eta$  is fixed to

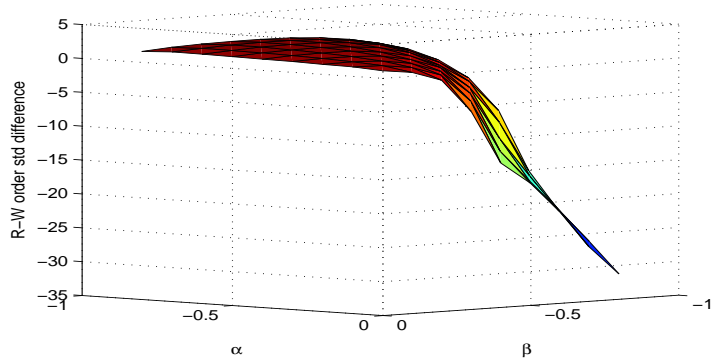


Figure 4: Impact of Supply Line Weighting on Order SD

0 based on the assumption that the customer demand process is known to both stages. We set  $a = 10$  and  $b = 100$ . Using the base order function (Section 3.2.1), we vary  $\alpha_b$  and  $\beta_b$  from 0.1 to 0.9 in increments of 0.1, respectively.

The difference in order standard deviations between the retailer and wholesaler under different weights on the inventory level and supply line is shown in Figure 4. The  $z$ -axis plots the wholesaler's SD minus the retailer's SD, while the  $x$ - and  $y$ -axes plot  $\alpha_b$  and  $\beta_b$ . It is evident from Figure 4 that there is a break at the line  $|\alpha_b| = |\beta_b|$ , that is, equal weighting between on hand inventory and the supply line. When  $|\alpha_b|$  is sufficiently larger than  $|\beta_b|$  (underweighting the supply line), the retailer's order SD on is smaller than the wholesaler's; that is, the BWE occurs. The less weight that is placed on the supply line, the greater the magnitude of the BWE will be. On the other hand, when  $|\alpha_b| < |\beta_b|$  (overweighting the supply line), the system exhibits RBWE. However, the magnitude of RBWE is insensitive to the weight placed on the supply line.

Our simulation confirms previous experimental studies on the relationship between the BWE and underweighting the supply line. On the other hand, in a recent survey by McKinsey [27], 65% of the 2990 responding executives believe that supply risk has increased during the past 5 years. These managers may rely more heavily on the supply line when making inventory decisions. This can diminish the magnitude of BWE or even create RBWE. As shown in our beer game experiment, when supply disruptions are a major factor, some players may change their behavior and put more emphasis on the supply line, resulting in RBWE.

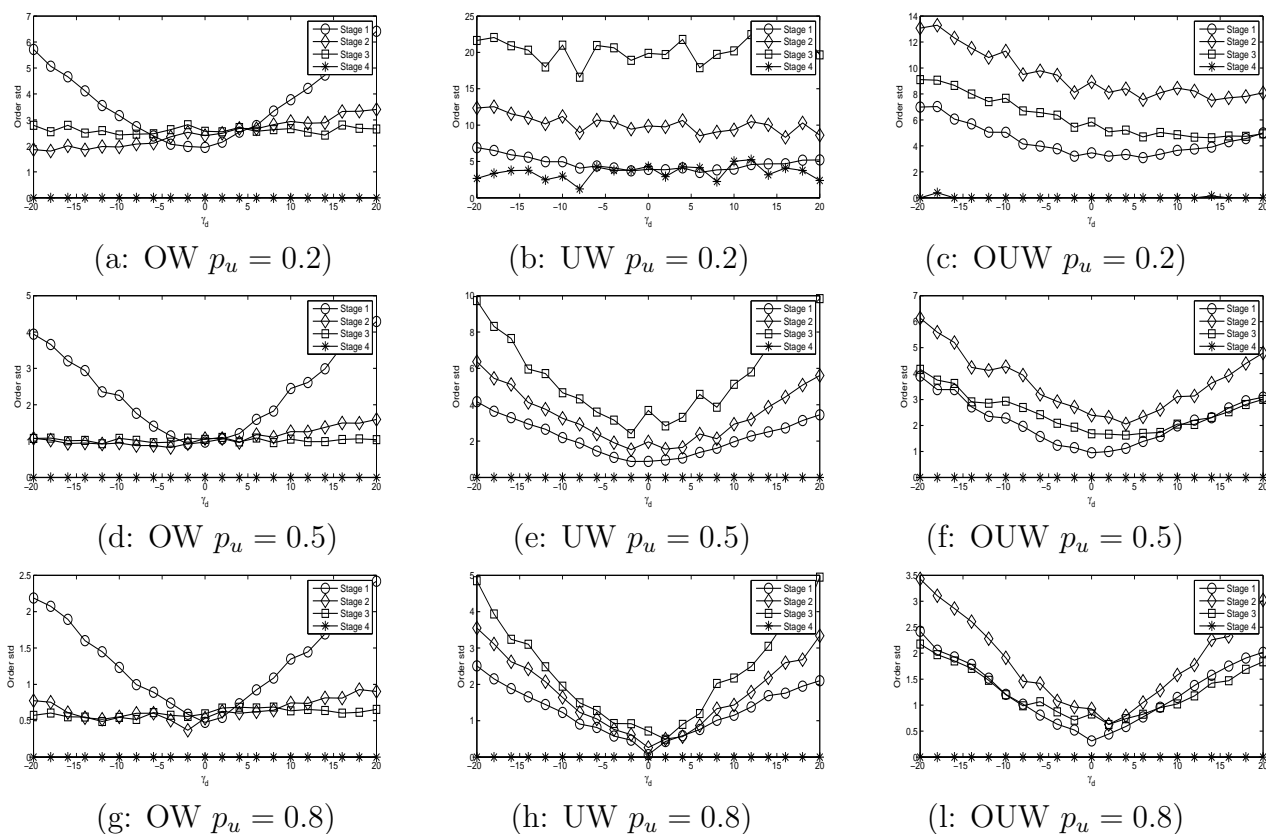


Figure 5: Effect of Stage 1's Reaction to Supply Disruptions

## 5.2 Simulated Behavior under Supply Disruptions

To examine the impact of supply disruptions in a serial supply chain, we use a 4-stage model, as in the beer game setting. The simulation study shows that the reaction to supply disruptions downstream serves as a trigger of order volatility. The relative weights between on-hand and supply-line inventory of each player largely determine the pattern of order standard deviations throughout the supply chain.

We use the disruption order function (Section 3.2.2) to model players' reaction to disruptions. Because the result in Section 3.2.2 indicates that downstream players usually react most to supply disruptions, we set  $\gamma_d \neq 0$  at stage 1 only; that is, only stage 1 changes its order quantity in response to disruptions. For the underweighting case,  $\alpha_d = -0.2$  and  $\beta_d = -0.1$ . For the overweighting case,  $\alpha_d = -0.1$  and  $\beta_d = -0.2$ . The choice of  $\alpha$  and  $\beta$  makes underweighting and overweighting significantly and keeps their value within the reasonable range that we observe in Table 3. The parameters  $\eta$ ,  $a_d$ , and  $b_d$  are set the same as their counterparts in Section 5.1.

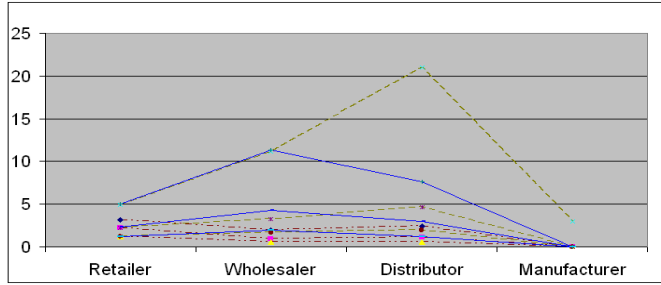


Figure 6: Simulated Order SD When  $\gamma_d = -10$

The capacity distribution is almost the same as in the beer game, except the the down-state capacity is fixed rather than random. The order placed by stage 4 is bounded above by  $\xi_d$  or  $\xi_u$  (depending on the state). We assume  $\xi_d < 50 < \xi_u$ .

We investigate three cases: 1) all stages overweight the supply line (OW); 2) all stages underweight the supply line (UW); 3) stages 3 and 4 overweight the supply line and stages 1 and 2 underweight the supply line (OUW). We vary  $\gamma_d$  to model stage 1's reaction to disruptions. The order SD of each stage during disruptions is shown in Figure 5. We fix  $\xi_u = 60$ ,  $\xi_d = 40$  and  $p_d = 0.1$  and vary  $p_u$  among 0.2, 0.5 and 0.8 to represent slow, medium, and quick recovery, respectively. Stage 4's order SD during disruptions is zero or close to zero because of the tight capacity.

From Figure 5, when  $\gamma_d = 0$ , there is still some order variability at all stages; i.e., the supply disruption transfers downstream. That is because the supply disruption affects the downstream stages through changes in its inventory level and supply line. But if the retailer does not react to disruptions (much), then the order variability is limited, especially when the disruptions are not severe.

When  $\gamma_d$  is large enough, the retailer generates sufficient demand uncertainty for his upstream partner. Underweighting the supply line then magnifies the order shock such that BWE appears from stage 1 to stage 3 consistently in case UW and from stage 1 to stage 2 consistently in case OUW. At the same time, overweighting the supply line can effectively reduce the order shock, which causes RBWE for the wholesaler and distributor in case OW and the distributor in cases OUW. However, the sign of  $\gamma_d$  is not an important factor in determining the order SD since the order SDs are quite symmetric in Figure 5.

Figure 6 depicts the order SD for each case in Figure 5, taken at  $\gamma_d = -10$ . It represents the general pattern of order SDs that can occur in the supply chain. The beer game experiment indicates that people may respond to supply disruptions differently. This is also shown

in Figure 6, where the order standard deviation can exhibit various types of curves. In reality, if the manufacturer and retailer have more control over the supply chain—for example, the manufacturer produces a popular brand and/or the retailer has the advantage of a strong sales channel, then companies close to the manufacturer may weigh the supply line more while companies close to the retailer may weigh the inventory level more. Consequently, the chance of having an “umbrella” pattern of order SDs is high.

Figures 5 and 6 indicate that the reaction to supply disruptions can be considered as a magnifying force, created by the supply disruption and propagating downstream. At the same time, overweighting the supply line can be treated as a dampening force that decreases vibrations that are propagating upstream.

### 5.3 Impact of Disruption Process

In the base and disruption order functions, it is the variability in the inventory level and supply line that creates order fluctuations during the supply disruptions. The inventory level and supply line are, in turn, highly dependent on the capacity process. However, we find that the order SD does not increase monotonically with respect to the failure rate. It usually reaches its highest point when the failure probability is roughly equal to 0.5. In contrast, the order SD decreases monotonically with respect to the recovery rate. Therefore, we conclude that the recovery rate has more impact on the order SD than the failure rate does.

We examine the impact of the capacity process on order variability in Figure 7. We set  $\gamma_d = -10$ . In parts (a), (b) and (c), we set  $p_u = 0.9$  and vary  $p_d$ , while in parts (d), (e) and (f), we set  $p_d = 0.1$  and vary  $p_u$ .

When the frequency of supply disruptions increases (parts (a), (b), and (c)), the order SD at each stage does not react monotonically. The number of up periods is a geometric distribution with parameter  $p_d$ . The mean and variance of the number of up periods decrease as the failure rate increases. The inventory level and supply line approach a stationary level when the number of up periods increases. If the failure rate is small, the variance of the number of up periods is large but the inventory and supply line become stable at the end of the last up period due to a high mean number of up periods. If the failure rate is large, the change in the inventory level and supply line is quick because the mean number of up periods is small, but the variance of the number of up periods is low. Therefore, the greatest fluctuation in the inventory and supply line at the beginning of the disruption is achieved

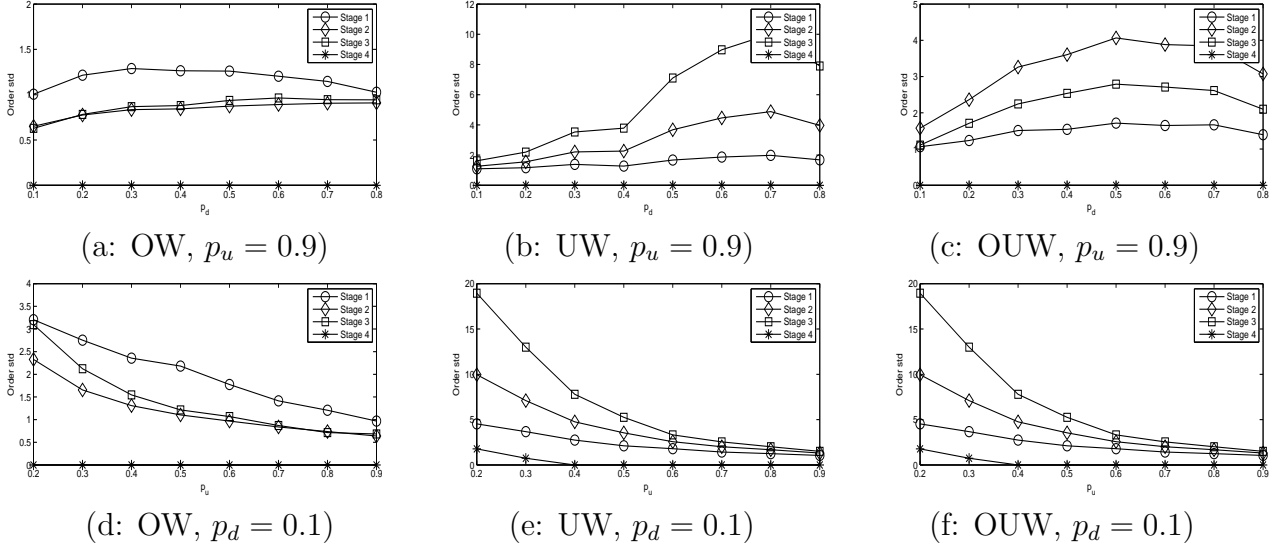


Figure 7: Effect of the Frequency of Supply Disruptions

when  $p_d \approx 0.5$ . This may be the reason why the order standard deviation reaches its highest point when the failure rate is in the medium range.

When recovery takes less time (parts (d), (e), and (f)), the order SDs at each stage decrease monotonically, because when the number of down periods increases, the inventory level decreases. This makes the order quantity increase by the number of recovery periods, which expands the range of order quantities. This may be the reason why the order SD is decreasing with the recovery rate.

In Figure 8, we set  $p_u = p_d$ ; that is, the stationary probability of being up and down is the same. We set  $\gamma_d = -10$ , and  $\xi_u$  and  $\xi_d$  to 65 and 45 to ensure that the overall capacity is sufficient to meet the demand. As  $p_u$  and  $p_d$  increase, disruptions become more frequent but shorter. As this happens, Figure 8 is closer to parts (d), (e) and (f) than it is to parts (a), (b), and (c) in Figure 7. This indicates that the recovery process dominates the disruption process in terms of order SD. This can also be verified from the magnitude of Figure 7, where the maximum value of the  $y$ -axis in parts (a), (b), and (c) is half of that in parts (d), (e), and (f)

## 6. Conclusion

People drive any business. Therefore, behavioral supply chain research addresses the question of how people behave in various settings and the effect of that behavior on the supply chain

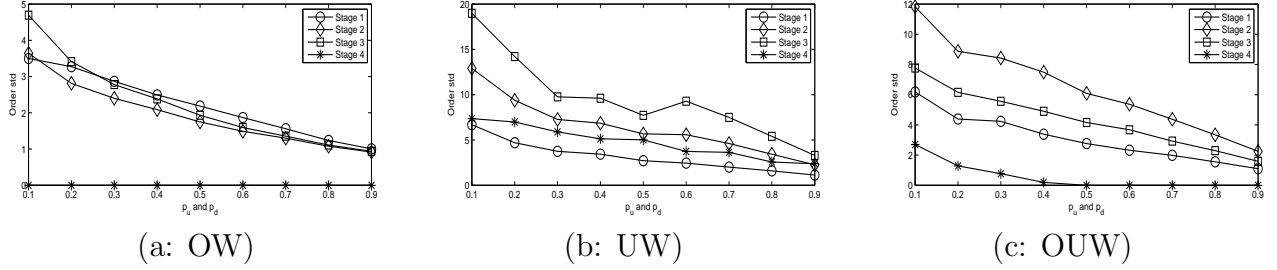


Figure 8: Effect of Frequency of Supply Disruptions with Equal Up and Down Probabilities

as a whole. Recent research on the beer game experiment explores basic elements of human decision making, such as underweighting of the supply line. However, it is impossible to find a universal behavior that all managers follow.

Our studies use a beer game experiment to learn about the structure of human decision making, then perform simulation studies to examine the relationship between individual behavior and order variance quantitatively. Our descriptive models can serve as a foundation for studies involving questions of supply chain design and management. Just as in queueing theory, in which human behaviors of patience and abandonment can be quantified and used to develop optimal rules for designing queueing systems, we believe that future research should be performed to answer questions about the optimal form of ordering decisions when other managers in the system behave in a certain way.

In a dynamic world, managers face uncertainty not only from the demand side but also from the supply side. The past several years have seen a range of high-profile disruptions or near-disruptions, including Y2K, September 11th, SARS, the Indian Ocean tsunami, and hurricane Katrina. These low-probability, high-impact events have a tremendous impact on the supply chain, as do smaller, less newsworthy disruptions that happen on a regular basis. In this paper, we studied potential forms of ordering behavior during disruptions by introducing supply uncertainty into the beer game and simulation experiments.

From our beer game experiment and simulation studies, we conclude that the BWE is not a ubiquitous phenomenon and suggest that a reverse phenomenon, the RBWE, often occurs because of supply disruptions. We have identified two independent ways to generate the RBWE: overweighting of the supply line, and overreactions to capacity shocks. The first causes the RBWE by smoothing the order pattern upstream. The second propagates supply disruptions downstream. Both causes provide some explanation as to why recent empirical studies have concluded that the BWE is not as prevalent as previously thought [3, 7].

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