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The Impact of Constrained Ordering Behavior on the Bullwhip Effect

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Abstract

In this thesis, we first discuss the concept and features of the bullwhip effect (BWE), followed with a literature review on the literature that study the rational and behavioral causes of the BWE and BWE's reaction to changes in the conditions. We presume that by imposing a certain order constraint on supply chain players, the BWE can be reduced. We test our conjecture using both a live "beer game" experiment and a simulation study. In the beer game, we find that the order constraint works the best when imposed on the distributors. In the simulation experiment, we find that the supply-line weighting type significantly impacts the effect of the order constraint. Moreover, our study provides guidance for models of operational disruptions by incorporating human reactions to order constraints.

Chapter 1

Introduction

1.1 Bullwhip Effect

The bullwhip effect (BWE), named by managers at Procter & Gamble and formally introduced by Lee et al. [14], is "the phenomenon where orders to the supplier tend to have larger variance than sales to the buyer (i.e., demand distortion), and the distortion propagates upstream in an amplified form (i.e., variance amplification)" [14]. The phenomenon has been observed in many supply chains. For example, Procter & Gamble's logistic executives, of course, found that there was extensive order amplification for Pampers, a brand of diapers, as they move up the supply chain, while the consumption rate was at a steady rate [13]. Hewlett-Packard's printer supply chain [13] and a clothing supply chain [8] showed the same phenomenon too.

The well-known "beer game" [18] is another good illustration of the bullwhip effect. The "beer game" has also stimulated a number of experiments that study the BWE from aspects like exploring the behavioral causes of the BWE and seeking effective methods to mitigate the BWE.

On the macroeconomics level, there also have been a number of studies that address industry-level BWE. The BWE was reported to be found in industries like the television set industry [11], automobile industry [2], machine tool industry [1] and many other industries. Terwiesch et al. [19] report that the semiconductor equipment industry has more pronounced BWE than the personal computer industry.

While there is certainly no lack of empirical evidence from the real world proving the existence of the BWE, recent evidence suggests that the BWE does not prevail in general. For example, in a study using industry-level U.S. data, Cachon et al. [4] find that the BWE exists in wholesale industries, but not in retail industries and most manufacturing industries. A number of recent studies using the beer game [5, 7, 6, 17, 15, 16] have find that, in at least a substantial portion of trials, the opposite effects occurs. Rong et al. [17, 15, 16] first introduce the reverse bullwhip effect (RBWE). Their studies show that under a rationing game or supply disruption, the retailers compete for scarce supply and the RBWE occurs between suppliers and retailers.

When the BWE happens, the instability of the supply chain increases, as a small change in the order quantity of the most downstream player, in most cases, the consumer can result in much larger changes in the orders that upstream players receive. This causes a waste of resources and increases in costs. The importance of mitigating the bullwhip effect in supply chains has been well recognized. Following most of the recent studies on the BWE, our study proposes that by adding a certain behavioral constraint to the supply chain players, the orderquantity variability can be reduced and thus the BWE can be mitigated. We test our conjecture using both a live beer game experiment and a simulation study.

1.2 Literature Review

Among the numerous studies about the bullwhip effect, we find they fall into three major categories. Most of the early research demonstrates the existence of the BWE. In recent years, many researchers have analyzed the rational and behavioral causes of the BWE, while some others investigate the BWE's reactions to certain changes in the environment. Since this thesis discusses behavioral methods to mitigate the BWE, we first review the literature on the causes of the BWE and then the literature on the BWEs reactions to changes in the environment.

Forrester [9, 10] was the first to conduct an extensive study on this variance amplification phenomenon. In his seminal book *Industrial Dynamics* [10], he reported the findings of demand information amplification in a supply chain, and concluded that two types of delays, namely demand information transfer delay and physical productions transfer delay through the supply chain, were the main causes of this demand amplification.

Lee et al. [13, 14] identified four major causes of the bullwhip effect: demand forecast updating, the rationing game, order batching and price variations. The authors analyze on how each of these four causes affects the supply chain, and provide possible solutions for these causes, which have subsequently been tested by many researchers through beer game experiments.

Other causes for the BWE have been identified. For example, external cost shocks, such as promotional discounts, will induce forward-buying behavior, which causes the bullwhip effect [3]. Seasonality can also cause the BWE; for example, Cachon et al. [4] found that industries with high seasonality are more likely to have a smoothed demand volatility while industries with no seasonality are more likely to have an amplified demand volatility.

In addition to these rational causes, there are also behavioral factors. For instance, Sterman [18] observes that players tend to ignore the supply line inventory while making decision; he calls this "underweighting" of the supply line. This factor was later demonstrated by Croson and Donohue [6] in a behavioral study. They found that even after removing all the typical rational causes (demand forecast updating, rationing game, order batching and price variations), the BWE still exists.

Studies on the BWE's reactions to changes in supply chain conditions are mostly based on the beer game. However, some researchers have introduced simulation approaches, which are efficient and easy to operate, considering the challenges to recruit sufficient people to play the live beer game. Past research using the beer game or simulation include but are not limited to the following.

Kaminsky and Simchi-Levi [12] shorten the order information transfer delay and physical productions transfer delay in the supply chain. What they see is a reduction in total supply chain costs, but not in the BWE.

Croson and Donohue [5] examine the impact of point of sale (POS) data sharing on the BWE. They show that, from a behavioral perspective, that sharing POS information does help reduce the BWE. Croson and Donohue [6] make the demand distribution known and stationary, which means the normal operational causes (e.g., batching, price fluctuations, demand estimation, etc.) are removed, but they find that the BWE still exists. They further find that if the inventory information is available to all players in the supply chain, the BWE is decreased.

Rong et al. [16] use a simulation study to study the reverse bullwhip effect (RBWE), and analyze the operational causes of the RBWE when the supply suffers from some uncertainty. Rong et al. build an order function under supply disruptions. Their study has inspired the author of the present thesis when designing the simulation experiment, which will be introduced in detail in Chapters 2 and 4.

1.3 Thesis Overview

The present thesis aims to study the behavioral side of the BWE's causes. We introduce the concept of rational order range and irrational order quantity. The rational order range is defined by the suppliers. Based on their experience and knowledge, in most cases, the consumer demands fall into this range, and so should the supply chain buyers' orders. An irrational order quantity refers to a quantity outside the rational order range, i.e., higher than the upper limit of the rational order range (we call this "over-ordering"), or lower than the lower limit of the rational order range (we call this "under-ordering"). To constrain the supply chain buyers from overreacting to consumer demand variations, the suppliers issue an irrational-order penalty. For any irrational order quantities, the buyers have to pay an irrational-order penalty in addition to all other expenses. We suppose that such a constraint would force the supply chain buyers to reduce their order variations, and thus smooth the BWE.

This constraint may sound a little unusual, but we believe it is applicable in the real business world. For example, let's say Tom, a fictional character who owes a fictional sports bar, doesn't watch soccer at all and has no idea what is going on with something called the World Cup. Then one morning in June, 2014, a waiter in his bar tells him that they should probably prepare a lot of beer, since the game between the U.S. and Ghana is kicking off at 3:00 pm that day. Tom is surprised yet he agrees. So when the daily beer delivery truck comes that day, Tom wants more beer than he normally would order. But the beer delivery man says: "Sorry, but all the bars want extra beer today. If you want that beer, you need to pay an extra charge." Tom then has to make a decision, whether to purchase extra beer or not. This decision depends on how much the extra charge is, and his prediction of how high the demand for beer will be, and how long the increased demand will last. Even though Tom and his sports bar are fictional, the reader can get an idea of how this constraint exists in the real business world.

We use both a live beer game experiment and a simulation study to test our hypothesis. The remainder of the thesis is organized as follows. In Chapter 2, we explain the experimental design and order functions for our experiments. Chapters 3 and 4 discuss the results of the live beer game and the simulation study, respectively. Last, we summarize our conclusions in Chapter 5.

Chapter 2

Basic Settings

The beer game experiment and simulation experiment in this thesis study a 4-stage serial supply chain under periodic review. Stages 1-4 correspond to the retailer, wholesaler, distributor, and factory, respectively. The beer game and simulation experiment last for 30 weeks (periods). The retailer receives demand from an external customer. Following Sterman [18], we set the demand from the customer at 4 beers/period for the first 3 weeks until it increases to 8 beers/period in the 4th week and remains at 8 until the end of the horizon.

In order to observe the reaction of the BWE to the changes in conditions, we keep the information and shipment lead times so that the BWE will be more evident. We assume that there are two weeks of information delay between every buyer/supplier pair, i.e., stage i receives order information two periods after the order is placed by stage $i-1$. We also assume that there are two weeks of shipping delay between every buyer/supplier pair, i.e., stage i receives the shipment that stage $i+1$ sent out two periods ago. For the factory, it takes two weeks for the workshop to finish a production order. The factory has no production capacity limit.

Figure 2.1: Information and shipment flows in the supply chain

Information Flow →

	2weeks		2weeks		2weeks		1week	
Retailer	↔	Wholesaler	↔	Distributor	↔	Factory	↔	Workshop
	2weeks		2weeks		2weeks		1week	

← Shipment Flow

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

1. For $i = 1, 2, 3$, the shipment from stage $i + 1$ shipped two periods ago arrives at stage i (that is, the lead-time is 2). If $i = 4$, stage $i + 1$ refers to the workshop in the factory, and the order stage i placed 2 periods ago is done and arrives at the factory.

2. For $i = 2, 3, 4$, The order placed by stage $i - 1$ two periods ago arrives at stage i. If $i = 1$, stage $i-1$ refers to the external customer and the order placed by stage $i-1$ in the current period arrives at stage i.

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.

5. Since our study focuses on the impact of constrained order behavior, we define a rational ordering range (m to n) and irrational-order penalty. When stage i chooses an order quantity that falls outside the rational ordering range, it incurs irrational-ordering penalties.

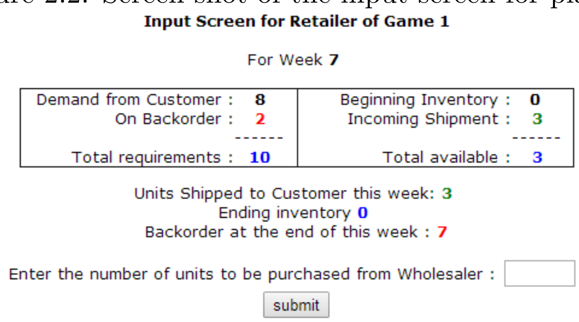
In order to examine the effect of the order constraint discussed in Chapter 1, we add the order constraint to one player in the supply chain at a time. We examine the presence of the BWE at each stage individually. Let σ_i be the standard deviation of orders placed by stage i across the time horizon. When $\sigma_i > \sigma_{i-1}$, stage i amplifies its order variability; i.e., the bullwhip effect (BWE) occurs at stage i. When the constraint is added to stage j, if the order constraint is effective in dampen order variations, we should find that for $i \geq j$, σ_i decreases compared to that standard deviation before adding the constraint; otherwise, the order constraint at stage j has no or negative effect in smoothing order variations.

In addition to discussing the effectiveness of the order constraint at stage i in mitigating the BWE, we compare the changes in σ_i before and after adding the order constraint, to discuss at which stage the order constraint works the best.

2.1 Beer Game Experiment Design

Our beer game experiment was conducted using a free online, web-based, automated beer game software, developed by Arunachalam Narayanan, hosted by the C.T. Bauer College of Business, University of Houston. Figures 2.2 to 2.5 shows the user interface of the software. Players can easily acquire information about their inventory/backorder position, incoming/outgoing shipments, order history, supply chain settings and cost for the current period and for the past 10 periods, i.e., weeks.

Figure 2.2: Screen shot of the input screen for players


Input Screen for Retailer of Game 1

For Week **7**

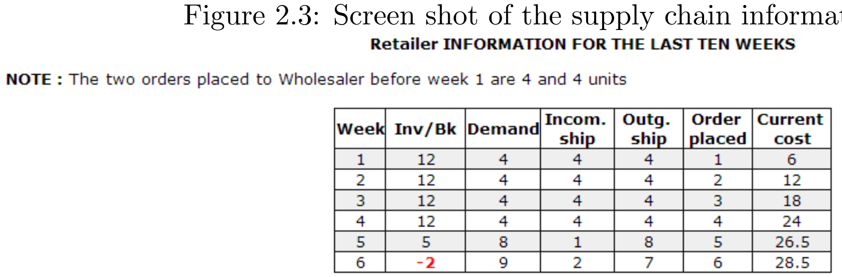
Demand from Customer : **8** On Backorder : **2** ------ Total requirements : **10**	Beginning Inventory : **0** Incoming Shipment : **3** ------ Total available : **3**

Units Shipped to Customer this week: **3**
Ending inventory **0**
Backorder at the end of this week : **7**

Enter the number of units to be purchased from Wholesaler :

submit

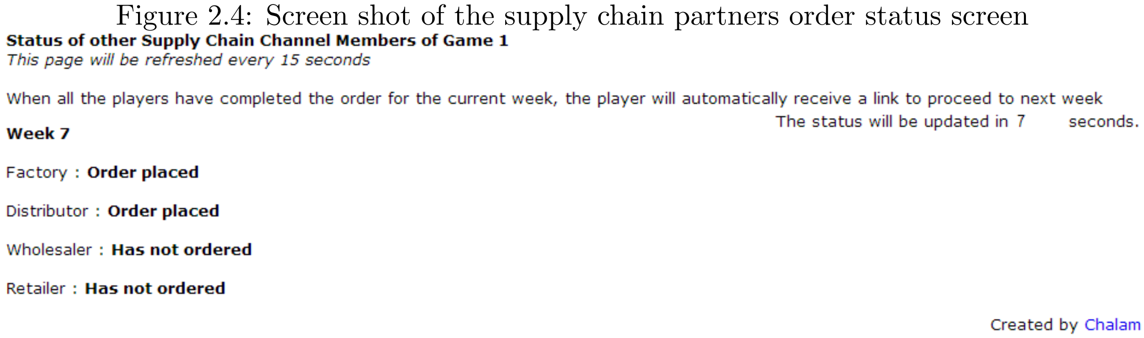
Figure 2.3: Screen shot of the supply chain information screen


Retailer INFORMATION FOR THE LAST TEN WEEKS

NOTE : The two orders placed to Wholesaler before week 1 are 4 and 4 units

Week	Inv/Bk	Demand	Incom. ship	Outg. ship	Order placed	Current cost
1	12	4	4	4	1	6
2	12	4	4	4	2	12
3	12	4	4	4	3	18
4	12	4	4	4	4	24
5	5	8	1	8	5	26.5
6	-2	9	2	7	6	28.5

Figure 2.4: Screen shot of the supply chain partners order status screen


Status of other Supply Chain Channel Members of Game 1
This page will be refreshed every 15 seconds

When all the players have completed the order for the current week, the player will automatically receive a link to proceed to next week

The status will be updated in 7 seconds.

Week 7

Factory : **Order placed**

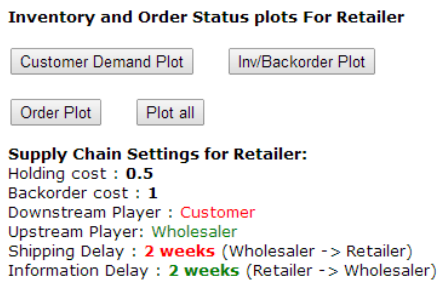
Distributor : **Order placed**

Wholesaler : **Has not ordered**

Retailer : **Has not ordered**

Created by Chalam

Figure 2.5: Screen shot of the plots and supply chain setting screen



Each player is randomly assigned to a team and role, and players do not know the team and role that the other players have been assigned to. No communication is allowed during the game. The software automates the information and shipment transfer process and transmits the order quantity and delivery quantity electronically. Compared to paper-based beer games, it speeds up the game and avoid communication errors.

The costs that occur in the game include the holding cost, backorder cost and irrational-order penalty. Following Sterman [18] and many other researchers, the holding cost is set to $ 0.5 and the backorder cost is set to $ 1. They are the same for all stages of the supply chain. To avoid order batching, there is no fixed order cost in the game and the unit price for beer is not considered.

The rational order range is 4 to 10. The irrational-order penalty was chosen to be $ 0.8 in the live beer game, for both over-ordering and under-ordering. This value was chosen because it is higher than the holding cost, so people would prefer to accept the holding cost ($ 0.5) than the penalty, which means that when people want to place an order that is less than the lower limit of the rational order range, they may prefer to increase their order quantity to the lower limit of the rational order range to avoid the penalty; and it is lower than the backorder cost ($ 1), so that players may decrease their order quantities if they are higher than the upper limit of the rational order range, since the penalty will be incurred.

However, when we built the simulation experiment after finishing the live beer game, we realized that since the penalty is less than the backorder cost, a rational player would tend to avoid any backorder cost even if he/she would have to pay the penalty. This suggests that the irrational-order penalty of $ 0.8 may not constrain the players over-ordering behaviors as well as it constrains the players' under-ordering behaviors. So in the simulation game, we adjusted the irrational-order penalty as follows: for under-ordering, the irrational-order penalty is $ 0.8; for over-ordering, the irrational-order penalty is $ 1.2. Such penalties can constrain the players' both under-ordering and over-ordering behaviors.

The beer game software we used does not allow the users to add new costs to the system, so the irrational-order penalty was not calculated automatically by the software. However, we emphasized this penalty before the game started, and kept it showing on the blackboard. From what the researchers have seen, the players did keep the irrational-order penalty in mind and were affected by it when making decisions.

Our live beer game experiments were conducted in the classrooms of two supply chain courses at Lehigh University, SCM 386 and IE 362. The experiments were improved by Lehigh IRB. The IRB project titles for the experiments are: *[491006-1] Supply Chain Disruption Study Based On The Beer Game and [562642-1] Supply Chain Study Based On The Beer Game*. There were 228 participants (57 teams of 4 players each) in total and they were all Lehigh University students. 4 participants didn't approve us to use their experiment results for the study in this thesis. Follow IRB's requirement, we removed their teams (4 teams in total) data from the results below. Most of the participants were undergraduate students and about 10 of them were graduate students. 208 participants were from Lehigh's College of Business and Economics, most of whom were not majoring in supply chain management but were required to take SCM 386. Because of the large number of students, SCM 386 offered 3 different sections at different times for the students to choose from. Based on the time of their classes, students were divided into 3 experiment groups, namely Group 1, Group 2 and Group 3. The other twenty participants were from the Department of Industrial & Systems Engineering, Lehigh University. They together formed Group 4, which were used as the control group. All the participants had some basic supply chain knowledge. But most had never heard of the beer game or the bullwhip effect before.

The participants were told that their goal was to minimize the total cost of his/her supply chain, not just his/her individual stage. During the game, the ranking of the teams kept refreshing on a screen that everyone could see. So even though there were no monetary incentives for the participants, the competitiveness of the participants and the encouragement from the professors who taught those courses were strong enough to push the participants to give their best try. 8 of the 20 participants (two teams) from Group 4 received potato chips after winning the game. The players on the first place team got to choose the flavor first. The potato chips was displayed on the front desk in the classroom and clearly had motivated the participants.

Each team played for up to 75 minutes. The introduction lasted 15 minutes, then the participants would play the game for two rounds. The first round is the normal beer game. Before the second round started, the researchers informed the students of the changes in the rules. In Group 1, Group 2 and Group 3, we added the order constraint to the retailer, wholesaler and distributor, respectively. The control group played the normal beer game one more time in the second round. The maximum number of periods that each team played is 36 for two rounds. However, many teams couldn't finish 36 periods for the second round. Considering that most teams finished 30 periods for each of the two rounds, to maintain consistency, the data after 30 weeks were discarded. We excluded teams who completed fewer than 30 periods in the first or second round of the game; 21 of the 53 teams are omitted from the results below.

In addition to the teams that didn't finish enough periods of the games, The factory in Team 6 in Group 1 had a mean order quantity of 4079.867, the retailer in Team 12 in Group 2 had a mean order quantity of 10769.57 and the retailer in Team 13 in Group 2 had a mean order quantity of 931.83, all of which are more than two standard deviations above the mean order quantity for all factories and retailers, and are significantly more than the mean customer demand of 7.47. Thus, the data for these teams were removed from the results below as well. Therefore, 15 teams from Group 1, 4 teams from Group 2, 8 teams from Group 3 and 2 teams from Group 4 were retained for subsequent analysis and will be presented below.

Despite the fact that in the live beer game experiment, the players' behaviors are the closest to decision makers' decisions in real business, as the psychological influences are kept, its inherent limits have made it difficult for us to draw general inferences from such an experiment.

Firstly, a team's performance is highly dependent on the behavior of all team players, and the players strongly affect each other. For example, in team 12, Group 2, the retailer intentionally placed orders for 10000 beers 3 times when the real customer demand was only 8 beers/period. His/her pranks made great challenges for his/her team members and his/her team ended up with a total cost of a few million dollars. Though this team's results have been omitted from our analysis, this shows how an individual's behavior influences the entire team.

Secondly, the time limit of the experiment limits the length of the games. The players need some time to get familiar with the game as well as the behavior pattern of their team members. In other words, it could take quite a few periods for the supply chain to arrive at a stable state. However, the time limit of the experiment prevented the teams from playing the beer game for two long enough rounds.

Another side effect of the experiment time limitation is that it reduced the sample size of the experiment. 21 out of 53 teams couldn't finish the whole experiment, which is a big loss for the study.

Next, the incentives in our beer game are different from those in a real business setting. In our beer game, the players were informed that it was the teams' performance, not their individual performance, which were measured. However, in the real business world, people would place their own profit at the highest priority. If we were in the real business world, we are afraid that the retailer of team 12, Group 2, would have behaved in a dramatically different way.

Lastly, the time and cost limits made it impossible to test all assumptions in the live beer game. For example, we couldn't test the effect of the order constraint on the factory, or on more than one player in the supply chain.

2.2 Simulation Experiment Design

We address these issues by implementing a simulation of the supply chain. In a simulation study, a computer operates all stages, following pre-defined ordering rules. The cost and time length to execute a simulation study is minimum; we can play the game for as many periods as we want, and we can also test all kinds of assumptions. Thus, our simulation study works as a complement and sensitivity analysis to our live beer game experiment.

The simulation study was conducted in an Excel spreadsheet the author built. It simulates a supply chain with almost the same settings as those in our live beer game experiment. The ordering rules follow Sterman's [18] model, and will be introduce in the next section.

2.3 Order Function

The most widely acknowledged order function is the one Sterman [18] postulated. He suggests that the order rate is indicated by the expected loss rate, corrected discrepancies between the actual and desired inventory level, and between the actual and desired supply line inventory level. The function is used as our model's *baseline order function*, and is as follows:

$$O_t^i = max\{0, EO_{t+1}^{i-1} + \alpha_b^i(DIL_t^i - IL_t^i) + \beta_b^i(DSL_t^i - SL_t^i)\}$$

Where the notation is as follows:

O_t^i: Order quantity placed by stage i in even 3.

EO_t^i: Expected demand from stage i in period t, forecasted by stage $i+1$ after event 2 in period $t-1$ using exponential smoothing:

$$EO_t^i = \rho O_{t-1}^i + (1-\rho)EO_{t-1}^i \ ,$$

Here ρ is the smoothing factor, $0 \leq \rho \leq 1$.

IL_t^i: Actual inventory level (on-hand inventory - backorders) at stage i after event 2 (i.e., after receiving incoming delivery from supplier and observing its demand but before placing its order or sending out shipment) in period t.

DIL_t^i: Desired inventory level. This value is pre-defined.

SL_t^i: Actual supply-line inventory level (on order inventory) at stage i after event 2 in period t. It represents all the inventory that stage i has ordered but hasn't received yet.

DSL_t^i: Desired supply line inventory level. This value is also pre-defined.

α_b^i and β_b^i: Fractional adjustment rage for the inventory level and supply line inventory level. The subscript b stands for "baseline". $0 < \alpha_b^i, \beta_b^i < 1$.

Sterman [18] discusses the supply line weighting reflected by the relationship of α_b and β_b. If $\alpha_b < \beta_b$, the supply line is overweighed; if $\alpha_b > \beta_b$, the supply line is underweighted. If $\alpha_b = \beta_b$, the supply line is equally weighted.

The order constraint that we would like to test will certainly change the order behaviors of players. So based on the baseline order function, we add new pressure. We introduce a new order function, which we call the *constrained order function.*

$$CO_t^i = max\{0, O_t^i + \gamma_c^i S_t\}$$

Where $O_t^i = max\{0, EO_{t+1}^{i-1} + \alpha_c^i(DIL_t^i - IL_t^i) + \beta_c^i(DSL_t^i - SL_t^i)\}$ is the estimated order quantity if not considering the order constraints.

S_t is the irrational order quantity and $S_t = max\{0, O_t^i - n\} + min\{0, O_t^i - m\}$;

Where n is the upper limit of the rational order range, and m is the lower limit of the rational order range.

$S_t < 0$, $S_t > 0$ and $S_t = 0$ represent over-ordering, under-ordering and rational ordering, respectively.

γ_c is a parameter representing how much of a penalty the players are willing to accept. $0 \leq \gamma_c \leq 1$.

If $\gamma_c = 0$, the players accept all order penalties;

$0 < \gamma_c < 0.5$, the players are very much willing to pay the order penalties;

$\gamma_c = 0.5$, the players accept 50% order penalties;

$0.5 < \gamma_c < 1$, the players are very much unwilling to pay the order penalties;

$\gamma_c = 1$, the players refuse any order penalties.

α_c^i and β_c^i: Fractional adjustment rage for the inventory level and supply line inventory level. The subscript c stands for "constrained". $0 < \alpha_c^i, \beta_c^i < 1$.

Under the order constraints, under-ordering costs more than holding inventory for 1 period, and over-ordering costs more than having the demand on backorder for 1 period. So players that are constrained will try to keep their orders within the rational order range, even if sometimes they need to accept some extra inventory or backorders. When the players find that they are going to over-order or under-order, they will adjust their order quantity in regards to how much they are unwilling to pay the irrational-order penalties.

Chapter 3

Beer Game Results

In the live beer game, we are interested in (1) whether or not the BWE is exhibited in the game, and (2) whether or not the order constraints helps damp the BWE in the supply chain, if we remove the learning effects. The control group, Group 4, was used to measure the learning effects.

3.1 The Existence of BWE

In our beer game setting, we kept the information delay and shipment delay and were expecting to see most of the players exhibiting the BWE. The results highly fit our conjecture. Table 3.1 lists the standard deviation of all players' orders in the first round of the game, for all the teams whose results were retained for analysis. The columns named C, R, W, D and F refer to Customer, Retailer, Wholesaler, Distributor and Factory, respectively. The ratios of the SD of stage i over stage $i-1 (i = 1, 2, 3, 4)$ (σ_i/σ_{i-1}) are also shown in the table. $i = 0$ corresponds to the external customer demand. If $\sigma_i/\sigma_{i-1} > 1$, stage i amplifies its order variability; i.e., the bullwhip effect (BWE) occurs at stage i.

As we can see from the table, 91.38% (106 out of 116) players exhibited the BWE in the first round of the game. The BWE happens at all stages in the supply chain. In the next section, we will present the results of the second round of the game, which can answer the question of whether or not the order constraints help damp the BWE.

Team	Customer	Retailer	σ_1/σ_0	Wholesaler	σ_2/σ_1	Distributor	σ_3/σ_2	Factory	σ_4/σ_3
Group 1									
Team 1	1.38	16.16	11.69	33.76	2.09	56.45	1.67	76.73	1.36
Team 2	1.38	26.02	18.81	98.37	3.78	233.14	2.37	291.47	1.25
Team 3	1.38	62.56	45.24	191.76	3.06	363.56	1.90	546.79	1.50
Team 4	1.38	25.58	18.50	25.52	1.00	64.56	2.53	498.83	7.73
Team 5	1.38	4.64	3.36	24.50	5.28	223.06	9.11	631.17	2.83
Team 7	1.38	181.20	131.02	97.01	0.54	96.38	0.99	116.50	1.21
Team 9	1.38	5.04	3.64	181.74	36.07	182.97	1.01	197.48	1.08
Team 10	1.38	23.49	16.99	185.39	7.89	38.53	0.21	56.22	1.46
Team 11	1.38	18.49	13.37	49.35	2.67	54.44	1.10	88.22	1.62
Team 12	1.38	10.59	7.66	27.53	2.60	38.26	1.39	68.35	1.79
Team 13	1.38	2.70	1.95	4.20	1.56	15.17	3.61	18.81	1.24
Team 14	1.38	7.45	5.39	9.13	1.22	97.93	10.73	102.80	1.05
Team 15	1.38	3.80	2.75	20.22	5.32	33.29	1.65	37.21	1.12
Team 17	1.38	4.85	3.51	15.07	3.11	62.19	4.13	248.00	3.99
Team 18	1.38	6.11	4.42	25.63	4.20	4.23	0.17	9.08	2.15
Group 2									
Team 5	1.38	14.17	10.25	7.64	0.54	14.01	1.83	15.16	1.08
Team 6	1.38	11.21	8.11	64.64	5.76	28.99	0.45	11.50	0.40
Team 15	1.38	4.33	3.13	23.75	5.48	8.01	0.34	15.44	1.93
Team 16	1.38	5.44	3.93	9.36	1.72	5.15	0.55	8.31	1.61
Group 3									
Team 1	1.38	10.41	7.53	30.60	2.94	145.77	4.76	187.20	1.28
Team 2	1.38	23.64	17.09	27.21	1.15	95.45	3.51	107.28	1.12
Team 4	1.38	9.97	7.21	6.10	0.61	15.89	2.60	26.10	1.64
Team 5	1.38	9.73	7.03	26.05	2.68	45.45	1.74	64.33	1.42
Team 6	1.38	18.05	13.05	12.87	0.71	37.74	2.93	70.46	1.87
Team 7	1.38	53.19	38.46	53.63	1.01	53.28	0.99	90.30	1.69
Team 10	1.38	9.94	7.19	103.19	10.38	161.95	1.57	179.00	1.11
Team 11	1.38	9.58	6.93	16.67	1.74	38.72	2.32	24.96	0.64
Group 4									
Team 4	1.38	6.06	4.38	12.78	2.11	16.28	1.27	26.90	1.65
Team 9	1.38	2.98	2.16	10.38	3.48	18.03	1.74	21.70	1.20
Mean		20.25		48.07		77.55		132.29	

Table 3.1: SD of orders for each player in the first round of the game

3.2 BWE and Reactions to Order Constraints

All four groups played the second round of game. For Group 1, Group 2 and Group 3, the order constraint were imposed on were on retailers, wholesalers and distributors, respectively. Group 4, the control group, played the normal beer game again in the second round of the game. We use the results of Group 4 to evaluate the learning effect of the participants in our beer game experiment.

Team	C	R	σ_1/σ_0	change	W	σ_2/σ_1	change	D	σ_3/σ_2	change	F	σ_4/σ_3	change
Group 1													
Team 1	1.38	2.10	1.52	-87.00%	6.87	3.27	56.62%	9.60	1.40	-16.48%	25.67	2.67	96.72%
Team 2	1.38	7.31	5.29	-71.90%	12.52	1.71	-54.72%	20.08	1.60	-32.31%	24.76	1.23	-1.37%
Team 3	1.38	5.87	4.24	-90.62%	12.63	2.15	-29.78%	14.73	1.17	-38.48%	27.79	1.89	25.45%
Team 4	1.38	3.93	2.84	-84.64%	3.87	0.99	-1.25%	6.11	1.58	-37.61%	15.92	2.61	-66.28%
Team 5	1.38	4.31	3.12	-7.10%	10.08	2.34	-55.70%	26.19	2.60	-71.47%	155.83	5.95	110.25%
Team 7	1.38	2.85	2.06	-98.43%	5.20	1.82	240.74%	6.59	1.27	27.42%	13.03	1.98	63.68%
Team 9	1.38	2.85	2.06	-43.45%	9.84	3.45	-90.43%	10.60	1.08	7.05%	10.39	0.98	-9.24%
Team 10	1.38	4.46	3.22	-81.02%	10.80	2.42	-69.33%	5.14	0.48	129.21%	8.29	1.61	10.54%
Team 11	1.38	2.78	2.01	-84.99%	7.46	2.69	0.73%	8.85	1.19	7.56%	31.55	3.56	119.89%
Team 12	1.38	2.25	1.63	-78.71%	1.01	0.45	-82.69%	15.10	14.88	970.71%	17.51	1.16	-35.10%
Team 13	1.38	1.02	0.74	-62.28%	2.19	2.15	37.86%	4.96	2.27	-37.06%	5.77	1.16	-6.32%
Team 14	1.38	3.95	2.86	-47.00%	3.83	0.97	-20.80%	12.48	3.26	-69.65%	18.73	1.50	43.00%
Team 15	1.38	2.00	1.45	-47.44%	13.70	6.85	28.89%	25.17	1.84	11.58%	30.40	1.21	8.07%
Team 17	1.38	2.19	1.58	-54.86%	2.32	1.06	-65.92%	18.14	7.82	89.61%	22.90	1.26	-68.34%
Team 18	1.38	4.17	3.01	-31.73%	7.91	1.90	-54.80%	17.65	2.23	1252.20%	22.52	1.28	-40.55%
Group 2													
Team 5	1.38	2.41	1.74	-82.98%	2.94	1.22	126.35%	4.96	1.69	-8.03%	6.95	1.40	29.42%
Team 6	1.38	5.03	3.64	-55.14%	3.70	0.74	-87.23%	4.18	1.13	151.60%	6.35	1.52	283.31%
Team 15	1.38	7.24	5.23	67.13%	23.37	3.23	-41.13%	19.65	0.84	149.48%	25.05	1.27	-33.89%
Team 16	1.38	0.96	0.70	-82.26%	2.06	2.14	24.07%	3.69	1.79	225.52%	4.48	1.21	-24.72%
Group 3													
Team 1	1.38	2.93	2.12	-71.86%	5.45	1.86	-36.76%	5.15	0.95	-80.14%	6.02	1.17	-9.00%
Team 2	1.38	2.63	1.90	-88.87%	3.62	1.37	19.45%	3.11	0.86	-75.48%	5.69	1.83	62.64%
Team 4	1.38	2.08	1.50	-79.15%	2.05	0.98	60.83%	6.66	3.25	24.94%	8.26	1.24	-24.45%
Team 5	1.38	5.76	4.17	-40.75%	9.82	1.70	-36.35%	10.08	1.03	-41.23%	16.06	1.59	12.61%
Team 6	1.38	2.31	1.67	-87.19%	3.36	1.45	103.63%	5.59	1.66	-43.22%	8.11	1.45	-22.25%
Team 7	1.38	12.58	9.10	-76.34%	12.81	1.02	0.97%	8.47	0.66	-33.50%	15.27	1.80	6.45%
Team 10	1.38	4.08	2.95	-58.94%	40.22	9.86	-5.08%	74.55	1.85	18.10%	90.57	1.21	9.93%
Team 11	1.38	6.98	5.05	-27.19%	18.07	2.59	48.92%	17.33	0.96	-58.73%	25.01	1.44	123.97%
Group 4													
Team 4	1.38	3.02	2.19	-50.06%	11.02	3.65	72.72%	5.83	0.53	-58.51%	11.20	1.92	16.33%
Team 9	1.38	2.45	1.77	-18.03%	8.25	3.37	-3.00%	13.90	1.68	-3.07%	16.81	1.21	0.50%
Mean	1.38	3.88			8.86			13.26			23.34		

Table 3.2: SD of orders for each player in the second round of the game and percentage changes compared to the first round

Table 3.2 contains the standard deviation of all players' orders in the second round of the game, the ratios of the SD of stage i over stage $i-1 (i = 1, 2, 3, 4)$ (σ_i/σ_{i-1}), as well as the percentage changes in σ_i/σ_{i-1}, compare to the first round of the game's results. If the percentage changes in σ_i/σ_{i-1} is negative, it means the BWE at the player decreased.

It is important to determine whether the above changes are because of the order constraints added in the second round of the game, or because the players became more familiar with the rules while playing the first round of game and behaved better when they had more experience. To answer these questions, we evaluated the learning effects of the participants in our beer game.

The learning effects are estimated as follows. The differences between the results of the two rounds of the game for Group 4 came from the learning process. We calculate the mean value of σ_i/σ_{i-1}, for $i = 1, 2, 3, 4$, for all players and both rounds of the games. The differences between the results of the first and second rounds of the game are numeric representations of the learning effect. If it is negative, it means that the player exhibited weaker BWE in the second round of game and suggests that this can be attributed to the learning effect.

Team	σ_1/σ_0 Round 1	σ_1/σ_0 Round 2	σ_2/σ_1 Round 1	σ_2/σ_1 Round 2	σ_3/σ_2 Round 1	σ_3/σ_2 Round 2	σ_4/σ_3 Round 1	σ_4/σ_3 Round 2
Group 4								
Team 4	4.38	2.19	2.11	3.65	1.27	0.53	1.65	1.92
Team 9	2.16	1.77	3.48	3.37	1.74	1.68	1.20	1.21
Mean	3.27	1.98	2.79	3.51	1.51	1.11	1.43	1.57
Learning Effect	-65.26%		20.38%		-36.09%		8.81%	

Table 3.3: Learng effects in the beer game experiment

It is a surprise to see that the wholesalers and factories exhibited even stronger BWE. But, it is reasonable. Firstly, the individuals behave quite differently from each other, and so are their learning capabilities. It is normal that some players improve more than others through the first round of the game. In addition, after the first round of the game, a player has learned, at least somewhat, his/her team members' order pattern. So in the second round, he/she will tend to adjust his/her strategies to cope with his/her team members'. But it's highly possible that his/her team members do the same thing. So the player's adjustment may not work as expected.

To remove the learning effect, we minus the average learning effect from the percentage changes in σ_i/σ_{i-1} in Table 3.2, and list the results in Table 3.4. The results are the change in σ_i/σ_{i-1}, for $i = 1, 2, 3, 4$, between the two rounds of the games, after removing the learning effects. The change can been interpreted as whether the BWE increased or decreased. If the change is negative, it means the BWE decreased (shown in table as "-"); if the change is positive, it means the BWE increased (shown in table as "+"). The results are summarized in Table 3.5, which lists the number of players in each role, each group, whose BWE increased or decreased in the second round of game.

Team	Change without Learning Effect	+/–	Change without Learning Effect	+/–	Change without Learning Effect	+/–	Change without Learning Effect	+/–
	Learning Effect: -65.26%		Learning Effect: 20.38%		Learning Effect: -36.09%		Learning Effect: 8.81%	
Group 1								
Team 1	-21.74%	–	36.24%	+	19.61%	+	87.91%	+
Team 2	-6.64%	–	-75.10%	–	3.78%	+	-10.18%	–
Team 3	-25.36%	–	-50.16%	–	-2.39%	–	16.64%	+
Team 4	-19.38%	–	-21.63%	–	-1.52%	–	-75.09%	–
Team 5	58.16%	+	-76.08%	–	-35.38%	–	101.44%	+
Team 7	-33.17%	–	220.36%	+	63.51%	+	54.87%	+
Team 9	21.81%	+	-110.81%	–	43.14%	+	-18.05%	–
Team 10	-15.76%	–	-89.71%	–	165.30%	+	1.73%	+
Team 11	-19.73%	–	-19.65%	–	43.65%	+	111.08%	+
Team 12	-13.45%	–	-103.07%	–	1006.80%	+	-43.91%	–
Team 13	2.98%	+	17.48%	+	-0.97%	–	-15.13%	–
Team 14	18.26%	+	-41.18%	–	-33.56%	–	34.19%	+
Team 15	17.82%	+	8.51%	+	47.67%	+	-0.74%	–
Team 17	10.40%	+	-86.30%	–	125.70%	+	-77.15%	–
Team 18	33.53%	+	-75.18%	–	1288.29%	+	-49.36%	–
Group 2								
Team 5	-17.72%	–	105.97%	+	28.06%	+	20.61%	+
Team 6	10.12%	+	-107.61%	–	187.69%	+	274.50%	+
Team 15	132.39%	+	-61.51%	–	185.57%	+	-42.70%	–
Team 16	-17.00%	–	3.69%	+	261.61%	+	-33.53%	–
Group 3								
Team 1	-6.60%	–	-57.14%	–	-44.05%	–	-17.81%	–
Team 2	-23.61%	–	-0.93%	–	-39.39%	–	53.83%	+
Team 4	-13.89%	–	40.45%	+	61.03%	+	-33.26%	–
Team 5	24.51%	+	-56.73%	–	-5.14%	–	3.80%	+
Team 6	-21.93%	–	83.25%	+	-7.13%	–	-31.06%	–
Team 7	-11.08%	–	-19.41%	–	2.59%	+	-2.36%	–
Team 10	6.32%	+	-25.46%	–	54.19%	+	1.12%	+
Team 11	38.07%	+	28.54%	+	-22.64%	–	115.16%	+

Table 3.4: Changes between Round 1 and Round 2 remove learning effects

Group	Change	R	W	D	F	Total	%
Group 1	Decrease	8	11	5	8	32	53.33%
	Increase	7	4	10	7	28	46.67%
Group 2	Decrease	2	2	0	2	6	37.50%
	Increase	2	2	4	2	10	62.50%
Group 3	Decrease	5	5	5	5	20	62.50%
	Increase	3	3	3	3	12	37.50%

Table 3.5: Summary of changes between Round 1 and Round 2 remove learning effects

Table 3.5 indicates that, in Group 1, the order constraint imposed on the retailers helped damp the BWE more than 50% of retailers, wholesalers and factories, but only at 1/3 of distributors did the constraint damp the BWE. In total, it helped 53.33% players decrease their BWE. In Group 2, the order constraint imposed on the wholesalers helped damp the BWE at 50% of retailers, wholesalers and factories, but it doesn't seem to work for distributors as all of the distributors' BWE increased. In total, it helped only 37.50% of players decrease their BWE. In Group 3, the order constraint added on the distributor helped dampen the BWE at 62.50% players in each role. In total, it helped 62.50% players decrease their BWE.

To summarize and answer the questions at the beginning of this chapter, we have seen 91.38% (106 out of 116) of players exhibited the BWE in the first round of the game (i.e., the normal beer game). After testing the order constraint on different supply chain roles, we found that the order constraint we proposed works the best when imposed on the distributors, as it helped 62.50% players decrease their BWE. It works positively in helping damp the BWE when it is imposed on the retailers, but it works negatively when imposed on the wholesalers.

Chapter 4

Simulation Experiment Results

In our simulation experiment, the game settings are almost identical to our live beer game experiment, except for the over-ordering penalty; as discussed in Section 2.1. The difference between the simulation experiment and the live beer game experiment is that the order decisions are made by the computer in the simulation experiment, but by humans in the live beer game. All the decisions were made using either the baseline order function or the constrained order function (see Section 2.3). Changing the parameters will change the order decisions. Since the customer demand pattern is stationary, for each setting of the parameters, there will be only one result of the simulation experiment. The demand is unknown to the supply chain, so the exponential smoothing factor ρ is set to 0.5. We set $DIL = 4$ and $DSL = 24$.

There are three parameters in the order functions: $\alpha_b(\alpha_c), \beta_b(\beta_c)$ and γ_c. By changing $\alpha_b(\alpha_c), \beta_b(\beta_c)$ and γ_c, we studied the relationships among the effects of the order constraints, supply-line weighting type and the willingness to accept the penalties.We select several settings of $\alpha_b(\alpha_c), \beta_b(\beta_c)$ and $\gamma_c$and test 12 scenarios.

For the supply-line weighting parameters, we set $\alpha_b(\alpha_c) = 0.1$ and $\beta_b(\beta_c) = 0.2, \alpha_b(\alpha_c) = 0.2$ and $\beta_b(\beta_c) = 0.1$ and $\alpha_b(\alpha_c) = 0.2$ and $\beta_b(\beta_c) = 0.2$ to represent underweighting, overweighing, and equal weighing, respectively.

We selected $\gamma_c = 0.25, 0.5, 0.75$ and 1, representing the players being very much willing to pay the order penalties, the players accepting 50% order penalties, the players being very much unwilling to pay the order penalties and the players refusing any order penalties, respectively.

In the simulation experiment, not only did we test the order constraint on the retailer, wholesaler and distributor, we also tested the order constraint on the factory. We simulate all possible combinations of the γ_c values and $\alpha_b(\alpha_c), \beta_b(\beta_c)$ values given above. Tables 4.1 to 4.6 show the results of the experiment.

α=0.1, β=0.2									
	Baseline	R Constrained	+/−	W Constrained	+/−	D Constrained	+/−	F Constrained	+/−
	ϒ=1								
σ_1/σ_0	1.13	1.13	=	1.27	+	1.13	=	1.13	=
σ_2/σ_1	1.28	1.28	=	1.26	−	1.28	=	1.28	=
σ_3/σ_2	1.32	1.32	=	1.31	−	1.32	=	1.32	=
σ_4/σ_3	1.19	1.19	=	1.17	−	1.19	=	1.19	=
	ϒ=0.75								
σ_1/σ_0	1.13	1.13	=	1.27	+	1.13	=	1.13	=
σ_2/σ_1	1.28	1.28	=	1.26	−	1.28	=	1.28	=
σ_3/σ_2	1.32	1.32	=	1.31	−	1.32	=	1.32	=
σ_4/σ_3	1.19	1.19	=	1.17	−	1.19	=	1.19	=
	ϒ=0.5								
σ_1/σ_0	1.13	1.13	=	1.27	+	1.13	=	1.13	=
σ_2/σ_1	1.28	1.28	=	1.26	−	1.28	=	1.28	=
σ_3/σ_2	1.32	1.32	=	1.31	−	1.32	=	1.32	=
σ_4/σ_3	1.19	1.19	=	1.17	−	1.19	=	1.19	=
	ϒ=0.25								
σ_1/σ_0	1.13	1.13	=	1.27	+	1.13	=	1.13	=
σ_2/σ_1	1.28	1.28	=	1.26	−	1.28	=	1.28	=
σ_3/σ_2	1.32	1.32	=	1.31	−	1.32	=	1.32	=
σ_4/σ_3	1.19	1.19	=	1.17	−	1.19	=	1.19	=

Table 4.1: The effects of order constraints under supply-line overweighting and various penalty acceptances

We can see from Table 4.1 that when the supply-line is overweighted, no matter how much the player is willing to accept the penalties, the order constraint only works if it is imposed on the

α=0.1, β=0.2					
Group		ϒ=0.25	ϒ=0.5	ϒ=0.75	ϒ=1
R Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	=	=	=
W Constrained	R	+	+	+	+
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-
D Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	=	=	=
F Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	=	=	=

Table 4.2: Summary of the effects of order constraints under supply-line overweighting and various penalty acceptances

α=0.2, β=0.2									
	Baseline	R Constrained	+/−	W Constrained	+/−	D Constrained	+/−	F Constrained	+/−
	ϒ=1								
σ_1/σ_0	1.59	1.59	=	2.10	+	1.59	=	1.59	=
σ_2/σ_1	2.01	2.01	=	1.81	-	2.01	=	2.01	=
σ_3/σ_2	2.39	2.39	=	2.13	-	2.39	=	2.39	=
σ_4/σ_3	2.76	2.76	=	2.40	-	2.76	=	2.62	-
	ϒ=0.75								
σ_1/σ_0	1.59	1.59	=	2.10	+	1.59	=	1.59	=
σ_2/σ_1	2.01	2.01	=	1.81	-	2.01	=	2.01	=
σ_3/σ_2	2.39	2.39	=	2.13	-	2.39	=	2.39	=
σ_4/σ_3	2.76	2.76	=	2.40	-	2.76	=	2.62	-
	ϒ=0.5								
σ_1/σ_0	1.59	1.59	=	2.10	+	1.59	=	1.59	=
σ_2/σ_1	2.01	2.01	=	1.81	-	2.01	=	2.01	=
σ_3/σ_2	2.39	2.39	=	2.13	-	2.39	=	2.39	=
σ_4/σ_3	2.76	2.76	=	2.40	-	2.76	=	2.69	-
	ϒ=0.25								
σ_1/σ_0	1.59	1.59	=	2.10	+	1.59	=	1.59	=
σ_2/σ_1	2.01	2.01	=	1.81	-	2.01	=	2.01	=
σ_3/σ_2	2.39	2.39	=	2.13	-	2.39	=	2.39	=
σ_4/σ_3	2.76	2.76	=	2.40	-	2.76	=	2.76	=

Table 4.3: The effects of order constraints under supply-line equal-weighting and various penalty acceptances

α=0.2, β=0.2					
Group		ϒ=0.25	ϒ=0.5	ϒ=0.75	ϒ=1
R Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	=	=	=
W Constrained	R	+	+	+	+
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-
D Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	=	=	=
F Constrained	R	=	=	=	=
	W	=	=	=	=
	D	=	=	=	=
	F	=	-	-	-

Table 4.4: Summary of the effects of order constraints under supply-line equal-weighting and various penalty acceptances

α=0.2, β=0.1									
	Baseline	R Constrained	↑/↓	W Constrained	↑/↓	D Constrained	↑/↓	F Constrained	↑/↓
	ϒ=1								
σ_1/σ_0	2.96	2.27	-	3.17	+	2.56	-	2.74	-
σ_2/σ_1	5.25	4.12	-	2.25	-	4.38	-	4.88	-
σ_3/σ_2	7.79	6.13	-	3.37	-	2.97	-	7.54	-
σ_4/σ_3	9.42	7.41	-	4.23	-	3.38	-	2.97	-
	ϒ=0.75								
σ_1/σ_0	2.96	2.27	-	3.42	+	2.65	-	2.76	-
σ_2/σ_1	5.25	4.12	-	2.48	-	4.68	-	4.97	-
σ_3/σ_2	7.79	6.13	-	3.72	-	4.48	-	7.64	-
σ_4/σ_3	9.42	7.41	-	4.67	-	5.20	-	5.27	-
	ϒ=0.5								
σ_1/σ_0	2.96	2.51	-	3.49	+	2.76	-	2.79	-
σ_2/σ_1	5.25	4.49	-	2.67	-	4.95	-	5.09	-
σ_3/σ_2	7.79	6.66	-	3.99	-	5.82	-	7.76	-
σ_4/σ_3	9.42	8.08	-	5.00	-	6.76	-	7.17	-
	ϒ=0.25								
σ_1/σ_0	2.96	2.93	-	3.66	+	2.87	-	2.87	-
σ_2/σ_1	5.25	5.17	-	2.75	-	5.07	-	5.14	-
σ_3/σ_2	7.79	7.59	-	4.20	-	6.85	-	7.74	-
σ_4/σ_3	9.42	9.16	-	5.18	-	8.16	-	8.45	-

Table 4.5: The effects of order constraints under supply-line underweighting and various penalty acceptances

α=0.2, β=0.1					
Group		ϒ=0.25	ϒ=0.5	ϒ=0.75	ϒ=1
R Constrained	R	-	-	-	-
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-
W Constrained	R	+	+	+	+
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-
D Constrained	R	-	-	-	-
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-
F Constrained	R	-	-	-	-
	W	-	-	-	-
	D	-	-	-	-
	F	-	-	-	-

Table 4.6: Summary of the effects of order constraints under supply-line underweighting and various penalty acceptances

wholesaler. It is very similar when the supply line is equally weighted (Table 4.4). The exception is, when the supply line is equally weighted and the factory is the player that is constrained, when the player is only willing to accept less than 50% penalties, the BWE at the factory decreases.

Table 4.3 shows that, when the supply-line is underweighted, the order constraint works in damping the BWE. Only when the wholesaler is constrained does the retailer's BWE increase. For all other scenarios, the BWE decreases. The order constraint seems to work the best in supply-line underweighting scenarios. The reason for this could be that players who under-weight the supply line tend to have more variable orders than players who don't, so that the order constraint has the greatest potential effect. In addition, a player's order behavior is influenced by his/her forecast of upcoming demands and shipments; although this forecast and the player's reaction to it are not captured explicitly in the order function, they are implicitly represented by the player's degree of supply-line weighting.

It is interesting to see that when the wholesalers are constrained, the retailers tend to exhibit even stronger BWE. In our live beer game, 50% of the retailers showed the same trend when the wholesalers were constrained. The reason for this phenomena can be an interesting topic for future researchers to study.

To conclude, our simulation experiment shows that the players' supply-line weighting type has a significant impact on the effect of the order constraints. When the supply-line is underweighted, the order constraints we tested have a significant influence on the BWE. When the supply-line is not underweighted, the order constraints work the best when imposed on wholesalers.

Chapter 5

Conclusion

In this thesis, we studied the effects of order-quantity constraints on the bullwhip effect (BWE). We tested these effects using both a live beer game experiment and a computer simulation of a supply chain. In the live beer game experiment, we found that the order constraint works the best when imposed on the distributors, as it helped 62.50% players decrease their BWE, but it would tend to increase the BWE when imposed on wholesalers. Our simulation experiment showed the relationships between the effect of the order constraint and supply line-weighting, the effect of the order constraint and penalty acceptance. We found that the players' supply-line weighting type has a significant impact on the effect of the order constraints. The constraint functions much better when the supply-line is underweighted. When the constraint is imposed on the wholesalers, the retailers show stronger BWE, but the wholesalers, distributors and factories' BWE are decreased.

This thesis is only the beginning of a comprehensive behavioral study of the effect of order constraints on the BWE. In the future, there is still a lot of work to be done to extend this thesis. The sample sizes in the live beer game experiment in this thesis can be enlarged, especially that of the control group. The constrained order function in the simulation experiment can be further developed. To a rational player, the decision of how much irrational-order penalties to accept is not only made by his/her a priori willingness, it is also highly dependent on his/her forecast of whether the backorder or low demand situation will continue. If he/she thinks that the low demand will continue, considering that the cost of holding extra inventory for many periods will eventually exceed the under-ordering penalty, he/she may be more willing to accept the under-order penalty. The constrained order function in this thesis cannot address this factor. In addition, we have seen that when the wholesalers are constrained, the retailers tend to exhibit even stronger BWE. Future studies can address the causes of this interesting phenomenon.

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Biography

The author was born in China in 1990. She was awarded a Bachelor of Management degree with honor in Beijing University of Posts & Telecommunications in 2012. Following that, she spent two years in studying Industrial & System Engineering in Lehigh University. Her professional experience includes working for Enterprise Systems Center, Accenture and China Unicom. By 2014, she finished his M.S. project in Lehigh University.