



Production smoothing in a serial supply chain: A laboratory investigation

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ABSTRACT

The purpose of this paper is to examine production smoothing in supply chains. Using the controlled setting of the laboratory, we systematically investigate supply chain features that lead to production smoothing. In contrast to prior laboratory studies of the bullwhip effect, we find that the bullwhip effect disappears in several of our experiments. More importantly, our study shows that when customer demand has a predictable seasonal component, retailers smooth orders. This behavior is more pronounced when changing order levels is costly. The results demonstrate how simplifying the structure of the supply chain leads to production smoothing behavior.

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1. Introduction

Managing a supply chain is a dynamic decision task shown to be prone to systematic errors, collectively referred to as the *bullwhip effect*. The bullwhip effect, which is the tendency for orders to become more variable as one moves away from the final customer and closer to the source of production, tends to lead to dysfunctional outcomes (Machuca and Barajas, 2004). For example, resources spent drilling for oil and gas fluctuate three times more than actual petroleum production, demand for machine tools is at least twice as variable as automobile sales (the auto industry being the main consumer of machine tools), and production of semiconductors is much more variable than industrial production as a whole (reported in Sterman, 2000, pp. 666–667).

Several logistics and supply chain studies have examined the bullwhip effect, as illustrated by Machuca and Barajas (2004), Haughton (2009), Wan and Evers (2011), Torres and Matz (2010), Xu et al. (2001), and Cachon et al. (2007). Certain supply chain factors contribute to the bullwhip effect (e.g., demand forecast updating, order batching, price fluctuations, and rationing) (Lee et al., 1997), and in fact other factors may mitigate it (e.g., restructuring the supply chain network) (Wan and Evers, 2011). A number of behavioral factors have also been shown to contribute to the bullwhip effect in the laboratory (e.g., poor team decision-making, lack of sharing of customer demand information, and mis-perception of feedback) (Sterman, 1989; Machuca and Barajas, 2004; Croson and Donohue, 2003, 2006; Wu and Katok, 2006).

There has been a long history of studies which have examined production smoothing (Blanchard, 1983; Blinder, 1986; Miron and Zeldes, 1988; Lee et al., 1997; Cachon et al., 2007). Briefly, production smoothing refers to the phenomena in which if firms face a cost to drastically change production levels, and when those costs exceed inventory holding cost, inventory should be used to smooth production. Stated differently, production smoothing is the decrease in standard deviation of orders as one moves-up the supply chain. Production smoothing has been documented in practice using aggregate data from the US Census Bureau (Cachon et al., 2007).

The purpose of our paper is to examine the cognitive reactions of individuals in a behavioral laboratory investigation of production smoothing in supply chains. In so doing, we respond to the call of Tokar (2010), Wan and Evers (2011), and Carter

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et al. (2007) for additional behavioral research in the logistics discipline. Tokar (2010, p. 1) and Wan and Evers (2011, p. 29) point out that logistics researchers should continue to incorporate behavioral factors into logistics models so that we can gain an increased insight on how human behavior, judgment, and decision-making affect supply chain performance.

We contribute to the production smoothing literature by examining the cognitive reactions of individuals in two-echelon supply chains that consist of a Retailer and a Factory. Our baseline treatment can be thought of as a simplified version of the beer distribution game (Machuca and Barajas, 2004; Serman, 1989). Our work builds-upon previous bullwhip and production smoothing studies because our experiment contains elements of seasonal demand and capacity constraints. We systematically manipulate these features in order to examine how individuals in our experiment react to the desired production smoothing phenomena.¹ We demonstrate that it is the interaction of seasonal demand and costly order changes (i.e., capacity constraints) which lead the individuals in our experiment to engage in order (production) smoothing behavior. Interestingly, we find in our simplified supply chain model that the laboratory participants made decisions which are consistent with our production smoothing expectations. We find that humans still intervene into the inventory management decision unless the supply chain system is simplified to two echelons. We believe that our results provide insight into the limits on human rationality and decision capability in a behavioral supply chain context. We also point out that our research contributes to prior vendor-managed inventory (VMI) research (Torres and Matz, 2010; Niranjana et al., 2011; Kaipia et al., 2006; Angulo et al., 2004; Yang et al., 2003). Stated differently, our research contributes to past VMI research because our study contains elements commonly found in VMI situations including the sharing of point-of-sale (POS) data and the direct shipment of inventory. Therefore, we examine the VMI phenomena by including elements of demand uncertainty and capacity constraints at the individual level of analysis.

The relative simplicity of a two-echelon supply chain laboratory experiment has upsides and downsides. Real supply chain structures are more complex (they are not simple serial chains, decisions are made by groups of managers, these decision-makers have access to ERP systems and other decision support tools, the decision-makers' incentives are unknown, etc.) Additionally, in many real-world supply chains, firms implement vendor-managed inventory (VMI) systems as a way to lessen the bullwhip effect (Torres and Matz, 2010; Niranjana et al., 2011; Kaipia et al., 2006; Angulo et al., 2004; Yang et al., 2003). But there is an important similarity to these field studies and our laboratory experiment. Managing both a real supply chain and a simulated laboratory supply chain are relatively complex (because supply chain partners in both settings may face issues of bounded rationality and opportunism (e.g., lack of trust) in the dynamic decisions that they make). To cope with these issues, decision-makers in both settings must, to one degree or another, rely on intuitive judgments because of cognitive limitations. Therefore, our laboratory experiment uses a simulated supply chain to examine the cognitive reactions of individuals to phenomena which exists in the field. In so doing, our study provides new insights about supply chain management. Indeed, it is difficult to measure factors that contribute to supply chain performance by using secondary data solely as was the case reported by Cachon et al. (2007).

2. Literature review

Our examination of the individual level issues of production smoothing is part of the broader realm of behavioral supply chain management research that is receiving increased attention in the supply chain discipline (Bendoly et al., 2010; Carter et al., 2007; Croson et al., 2011; Croson and Donohue, 2006; Tokar, 2010). Indeed, Carter et al. (2007) point out that more research is needed that integrates human judgment and decision-making theory into the traditional theoretical paradigms of supply chain management including the supply management field. Scant behavior research exists at the individual level of analysis within the production smoothing literature. The examination of production smoothing has been examined using field level data at the firm or industry level of analysis. For the purposes of this study, our literature review primarily focuses on production smoothing and bullwhip effect studies in the supply chain literature to show that limited research exists at the interface of the fields of behavioral supply chain management and production smoothing. In this section, we briefly summarize this body of research.

2.1. Production smoothing studies

A steady stream of production smoothing empirical research exists. At the industry level of analysis using US Census data, Cachon et al. (2007) suggests that production smoothing is more pronounced than the bullwhip effect because retailers have found ways to smooth their ordering behavior to reduce variability in the supply chain. Retailers do so because they incur additional order processing costs when their orders exceed normal demand variation (Balakrishnan et al., 2004). The Cachon et al. (2007) study was motivated in part because prior empirical research in economics found evidence that production is more variable than sales. For example, Blanchard (1983) empirically examines the production smoothing phenomena in the automobile industry and found inventory behavior is unstable thus resulting in the variance of production to be larger than the variance of sales. Blinder (1986) also found empirical evidence that the basic idea of production smoothing is all wrong. Thus the Cachon et al. (2007) study presents recent evidence to support the production smoothing hypothesis.

¹ The bullwhip effect and production smoothing are two sides of the same phenomena. Indeed, production smoothing is the opposite phenomena of the bullwhip effect.

2.2. Behavioral bullwhip studies

There is a growing interest in using controlled human experiments to examine supply chain phenomena (Bendoly et al., 2010; Carter et al., 2007; Croson et al., 2011; Croson and Donohue, 2006; Tokar, 2010). An examination of the bullwhip effect is one area of significant research interest (Croson and Donohue, 2006). For example, in a laboratory experiment involving the beer game, Machuca and Barajas (2004) found that EDI transmissions do lead to substantial supply chain cost savings when implemented across the whole supply chain. Similarly, Steckel et al. (2004) found that POS information sharing improved supply chain performance. Croson and Donohue (2006) suggest that sharing dynamic inventory information up the supply chain can provide a greater benefit than sharing inventory information down the supply chain. Lastly, Cantor and Macdonald (2009) show that an individual's cognitive thinking approach affects beer game performance.

2.3. Primary purpose and contribution of study

While the above mentioned studies, among many others, have made important contributions to the literature, a further examination of factors that contribute to production smoothing is needed. Therefore, the purpose of our paper is to examine the cognitive reactions of individuals in a behavioral laboratory investigation of production smoothing in supply chains. Specifically, while production smoothing has been a documented finding at an *aggregate* level of analysis (e.g., Cachon et al., 2007), the production smoothing phenomena has not been investigated at the *individual* level in the controlled setting of the laboratory. Therefore, we make several contributions to the behavioral supply chain management and production smoothing literature. First, our study is the first examination of the production smoothing phenomena in the laboratory setting. Second, we examine the cognitive reactions of individuals in supply chain situations where production capacity constraints exist in addition to predictable customer demand patterns (e.g., seasonal demand) in a laboratory setting. These supply chain structural factors have been shown to contribute to production smoothing in prior field supply chain studies but not in the laboratory (e.g., Cachon et al., 2007). Past studies have shown that the bullwhip effect (and not the production smoothing phenomena) has been a consistent finding in laboratory studies. Third, we extend past supply chain laboratory studies (e.g., Croson and Donohue, 2006) by incorporating factors that exist in the field into our experiment including capacity constraints and seasonality demand conditions. Previous supply chain laboratory studies have not examined the impact of order costs on supply chain performance. Further, prior studies assume that customer demand is stationary and not seasonal, as is the case in this study. Fourth, we examine the limits of human rationality and decision capability in the context of a production smoothing problem. Our study seeks to fill these voids in the literature.

3. Hypotheses

Before we present our research hypotheses in this section, we provide a definition of production smoothing and the bullwhip effect. As mentioned earlier, production smoothing is defined as the decrease in standard deviation of orders as one moves-up the supply chain. Stated differently, if order or production smoothing exists, then the standard deviation of orders of the i th echelon in the supply chain, σ_i , is less than its immediate customer σ_{i-1} , (for all $i \in \{R, F\}$). If amplification (bullwhip) exists, then the standard deviation of orders of the i th echelon in the supply chain, σ_i , exceeds that of its immediate customer σ_{i-1} (for all $i \in \{R, F\}$).

We now turn to our first set of hypotheses which examines the effect of two demand distributions on the bullwhip effect and production smoothing without order costs.

3.1. Demand distributions

A burgeoning amount of research is finding evidence that decision-makers suffer from cognitive blind-spots or limitations in supply chain laboratory experiments (Wu and Katok, 2006; Croson and Donohue, 2006; Croson et al., 2011). It is important to examine cognitive biases in the laboratory because despite the proliferation of sophisticated decision support tools in practice supply chain decision-makers continue to face difficulty in understanding how to identify the optimal ordering policy. Therefore, Wu and Katok (2006), Croson and Donohue (2006), Croson et al. (2011), among many others, have continued to examine how and why supply chain decision-makers suffer from cognitive biases. Indeed, these studies purport that decision-makers rely on experience and intuition to understand customer demand patterns because of internal and external constraints which prevents the decision-maker from following the optimal ordering policy. In so doing, these studies report poor supply chain performance in the form of the bullwhip effect. As such, even in the controlled environment of the beer game, there is no evidence that participants in any of the beer game studies reported to date follow the optimal ordering policy – i.e., the base-stock policy. Although optimal policies can be derived theoretically (although usually assumptions required are quite strong) they may not be transparent to subjects in laboratory beer games. In fact, regardless of the demand function communicated to beer game participants including the Croson et al. (2011) constant demand of 4, there is little empirical evidence that participants adhere to the game's demand distribution. Following this logic, it is plausible that the participants in our study are not readily capable of processing the data that is provided to them and as a result face cognitive limitations in their ability to determine optimal order quantities.

Supply chain participants may not follow the optimal ordering policy because they do not trust their team members. Croson et al. (2011) for example find the bullwhip effect in settings with constant and known customer demand of four units per week persists even in a treatment in which participants are told that the cost-minimizing policy is to always order the same amount as the order received. Even though players understand the optimal solution, these individuals do not believe that other team members understand it as well. Consequently, many players seek additional safety stock because they do not trust their supply chain partners, thus setting off a cycle of backlogs.

The problem of cognitive biases is also acute in supply chains in which the optimal ordering policy is completely transparent. Croson et al. (2011) report on an experiment with the beer game where customer demand is explicitly communicated to all laboratory participants (i.e., demand is known and constant at four units per week with zero on-hand inventory and four units in each delay position). Simply ordering four units every period is guaranteed to result in the total cost of zero—the lowest possible cost. And yet not a single team in the Croson et al. (2011) study succeeded in following this policy which may have been in part due to the fact that the teams could not collaborate with one another. Even in a treatment in which three of the four supply chain members were automated and programmed to follow the base-stock policy, the majority of human decision-makers still deviated from the constant order of four units per week. Clearly, even in this seemingly transparent setting, the optimal policy is not obvious.

Supply chain decision-making should improve when individuals are provided with supply chain specific communication and training practices. However, Wu and Katok (2006) offer another piece of evidence that supply chain decision-makers continue to suffer from cognitive limitations even when training and communication practices are provided. In the Wu and Katok (2006) study, they report that in the treatment in which pre-game communication was allowed, a few (by no means all) of the teams decided to follow a policy in which the retailer carries all the safety stock, placed a constant demand of four units, and the rest of the supply chain members carry no safety stock and also order four units per period. This order smoothing policy is not optimal in a standard beer game (i.e., stationary demand distribution) but it has an advantage of being highly robust.

We propose that simplifying the structure of the supply chain and incorporating capacity constraints can reduce the cognitive burden that beer game participants have experienced in past laboratory studies. In so doing, we believe that creating an environment where the optimal ordering policy is transparent will either mitigate or even eliminate the bullwhip effect. In our first study, we examine whether the bullwhip effect is eliminated when we simplify the structure of the supply chain by creating a supply chain of only two echelons (rather than the customary four echelons). We also incorporate in our simplified supply chain design short lead times (2 periods between the Retailer and the Factory and 1 period production delay for the factory). We also examine how laboratory participants react to both Stationary and Seasonal demand patterns. In fact, the *Seasonal* (cyclical) demand pattern can be considered even more transparent to our participants than the *Stationary* demand distribution because *Seasonal* demand exists where demand is 8 in odd-numbered periods and 0 in even-numbered periods. We expect that the *Seasonal* demand pattern should be easy to predict and follow, and thus less cognitively complex than our *Stationary* demand function.

The simplified design of our supply chain provides a minimal cognitive burden for supply chain participants. In fact our supply chain design may provide an even more transparent way for our Retailer and Factory supply chain members to understand the optimal ordering policy as compared to more traditional supply chain designs (i.e., the Croson et al., 2011 study). Our simplified design may also provide an environment where each team member will more likely trust each other to follow the optimal ordering policy since there are only two supply chain partners who work together on the ordering task. The implication of simplifying the supply chain is that cognitive limitations are a function of the complexity of the supply chain. By making supply chains more transparent and instituting economic incentives, supply chain decision-makers should more likely behave according to basic inventory theory. Specifically, when order changes are costless, we know from Chen (1999) that it is optimal to follow a base-stock policy, and hence we should not see the bullwhip effect. Stationary demand in our experiment is a uniform integer from 0 to 8 which is communicated to our participants. Following this logic, we present the following two hypotheses.

Hypothesis 1A. In a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution is known and stationary (does not have a seasonal component).

Hypothesis 1B. In a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution has a seasonal component.

As mentioned above, because prior studies have found that beer game participants suffer from cognitive limitations which can be attributed to several laboratory design factors, we now compare the effect of volatility in customer demand in our simplified supply chain. Our supply chain design thus far has reduced several sources of complexity (e.g., number of echelons and lead-times). Our next hypothesis examines how our beer game participants react to volatility in customer demand on an additional performance metric, order variability. We would expect that the *Seasonal* distribution of customer demand can contribute to more volatility of ordering behavior compared to the *Stationary* distribution of customer demand. In our setting, *Seasonal* demand more than doubles the variance of the *Stationary* demand pattern. The variance of customer

demand in the treatments with *Seasonal* demand is 16.64 (standard deviation = 4.08), and in treatments with *Stationary* demand the variance is 7.22 (standard deviation = 2.68). Unless players significantly smooth production, this increased variability of customer demand should increase the variability of orders in general. In both the *Stationary* and *Seasonal* settings, consistent with Chen (1999), we would expect our supply chain participants to follow the base-stock policy.

It should be noted that under certain circumstances laboratory participants will smooth orders when faced with *Seasonal* demand. Since *Seasonal* demand is predictable and cyclical (i.e., alternates between 0 and 8 every period), it is plausible that the laboratory participants should not become cognitively overwhelmed by this demand distribution and may recognize that it could be desirable to smooth orders by constantly ordering four units of inventory every period. Laboratory participants may arrive at this decision because the *Seasonal* demand pattern is more transparent to both supply chain partners than *Stationary* demand (i.e., customer demand information is shared). Therefore, it is easy for the laboratory participant to calculate a smoothing order policy since we intentionally examine the seasonal component without a random component (e.g., it should be intuitive for the laboratory participants to calculate and place orders for four units of inventory each period).

As pointed out in Chen (1999), assuming that the laboratory participants follow the base stock policy (or some variation thereof) and don't calculate the smoothing policy, we believe that the greater volatility of *Seasonal* demand will lead to greater order variability in orders given the larger standard deviation of orders for *Seasonal* demand. Thus, we offer the following hypothesis.

Hypothesis 2. In a two echelon supply chain, when order changes are costless, order variability should be higher in the *Seasonal* demand setting as compared to the *Stationary* demand setting.

3.2. The cost of changing order amount

As highlighted earlier, there is a long history of empirical research into production smoothing – a phenomena in which if firms face a cost to drastically change production levels, and when those costs exceed inventory holding cost, inventory should be used to smooth production. Cachon et al. (2007) find that production smoothing is especially prevalent in industries which exhibit demand volatility (e.g., seasonality). The firm will produce at a reasonably constant rate throughout the year building inventory during the low season and drawing down inventory during the high season.

Informed by field studies on production smoothing, we propose that incorporating production costs into the beer game will help mitigate over-ordering behavior and thus improve the cognitive responses of the laboratory participants. We propose a supply chain design in which participants are charged a cost to change order quantities. This proposed supply chain design can incentivize the laboratory participant to make ordering decisions that are consistent with the optimal ordering policy. We also believe the effect of order change costs will be more pronounced on order smoothing when subjects are presented with seasonal demand as compared with stationary demand. In the *Seasonal* demand condition, laboratory participants may elect to smooth their orders because the *Seasonal* demand pattern is predictable and shared with both supply chain partners. Moreover, when faced with order change costs, laboratory participant will become more incentivized to calculate a smoothing order policy because of the potential financial ramifications of not doing so. Therefore, consistent with Sobel (1969) and Cachon et al. (2007), we would expect an interaction effect between costly order changes and the *Seasonal* demand setting on order or production smoothing. Based on these arguments, we offer the following hypothesis.

Hypothesis 3A. In a two echelon supply chain, when order changes are costly and the demand setting is *Seasonal*, order smoothing should occur.

Hypothesis 3B. When order changes are costly and the demand setting is *Stationary*, order smoothing should not occur.

4. Design of the experiment

We conducted a laboratory experiment to examine production smoothing in supply chains. Our experimental setting is a two-echelon serial supply chain, with a *Retailer* and a *Factory* with exogenous customer demand. Those readers familiar with the Beer Distribution Game will recognize our setting as a 2-echelon version of the game with fewer order and shipment delays. Fig. 1 shows the diagram of the supply chain in our experiment. Assigned the role of either a *Retailer* or *Factory*, each participant manages her own inventory by placing orders to the upstream supplier for replenishment so as to satisfy demands downstream over multiple periods. The role of end-customer is automated in our supply chain.

Each period begins with the arrival of shipments, which increases one's on-hand inventory. Next, orders placed by the downstream customer are received, which are either filled when inventory is available or become backlogged. Each participant (i.e., the participant plays the role of either the *Retailer* or the *Factory*) then makes an ordering decision and carries any remaining inventory/backlog over to the next period. The decision task is complicated by the existence of lead-times/delays in the supply chain. All participants saw, on their computer screens, their current inventory, previous order amount placed, customer demand, current amount on backorder, incoming shipments and orders, and total inventory and backorder cost. History on one's own inventory level, orders received and placed is also displayed to participants.

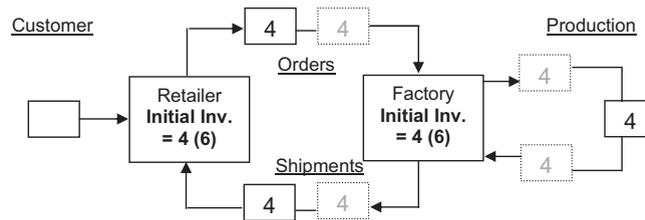


Fig. 1. The structure of the 2-echelon supply chain in our study. The solid boxes represent lead times in the short lead-time treatments. The dotted boxes were added in the long lead-time treatment. Each delay position was always initialized with four units. Initial inventory was four units in the short lead-time treatments and six units in the long lead-times treatments. The customer demand was $U(0, 8)$ and an integer in the stationary demand treatments and alternating at 0 and 8 in the seasonal demand treatments.

Table 1
Description of the factors and sample sizes in the treatments in our experiment.

Demand	Order change cost	Sample size (N)
Stationary	None	14
Seasonal	None	11
Stationary	Costly	15
Seasonal	Costly	13

Lead times: 2 = retailer; 1 = factory, demand: stationary = uniform integer from 0 to 8, seasonal = alternating 0 or 8, order change: costly = 0.5 tokens per unit of change, none = 0, sample size: number of pairs in the treatment.

We initialized orders and shipment in process to be four units. Starting inventory at each echelon of the supply chain was four units. Each team was given an initial monetary endowment, and all participants incurred inventory cost of 0.5 token per unit per week and backorder cost of 1 token per unit per week. Additionally, in treatments with costly order changes (e.g., any change in order quantity) the order change cost was 0.5 tokens per unit of change in order quantity (for example, an increase from 4 to 6 units or a decrease from 4 to 2 units cost 1 token). Note that this cost structure (equal per/unit cost of decreasing and increasing orders) is not meant to capture a cost structure one might expect to encounter in practice—increasing production, for example, is likely to be more costly than decreasing it, and additionally, increasing production may often require a fixed investment. In our experiment, however, we intentionally abstract away from these operational details and focus simply on the effect of having simple costs associated with changing orders.

Final team earnings in tokens were the difference between the initial team endowment and the cumulative holding, backorder, and where applicable order change costs, of all team members. Each participant is provided with real-time information as to their status on each of these cost components. At the end of the session, each team's total earnings were converted to US dollars at a pre-determined exchange rate and divided equally between the two team members. Our exchange rate was 630 tokens per dollar. Each participant earned about 9500 tokens from the game. Each participant was provided an additional \$5.00 show-up fee. All experimental sessions lasted 50 periods to make sure the game was long enough to allow the subjects to recover from any initial shocks. Previous experiments typically used about 38 periods with supply chains of four participants (Sterman, 1989; Machuca and Barajas, 2004; Croson and Donohue, 2003, 2006; Wu and Katok, 2006; Cantor and Macdonald, 2009).

Our design manipulates two factors that we summarize in Table 1. All treatments include the following lead times: 2 periods between the retailer and the factory and 1 period production delay for the factory. In our experiment, we test two different cost structures. In the condition with Costly order changes, there is a per-unit cost for changing the order from what it was in the previous period. Also within our experiment we have two demand distributions: in the Stationary demand condition customer demand follows the Uniform distribution from 0 to 8 (rounded to the nearest integer) and in the Seasonal demand condition demand is 8 in odd-numbered periods and 0 in even-numbered periods. Note that the Seasonal demand condition not only adds a seasonal component but also eliminates the random component from the customer demand distribution. Eliminating the random component eliminates the need for safety stock – just as in Croson et al., 2011 where demand is known and constant – and thus significantly simplifies the problem². We recognize that the seasonal demand treatments are not meant to literally capture seasonal demand settings in practice—of course in practice when demand is seasonal it also has a random component. Our goal is to isolate the seasonal component, and thus focus on behavior under seasonal demand not confounded by randomness. So we expect that our results will be the strongest within this seasonal demand condition.

In total, 106 participants were included in our experiment, each randomly assigned to one of the four treatments summarized in Table 1, as well as to one of the two roles (Retailer or Factory). We conducted all sessions at the Laboratory for

² Because the participants have access to downstream customer demand information, we believe that the seasonal demand pattern should be transparent to the beer game participant.

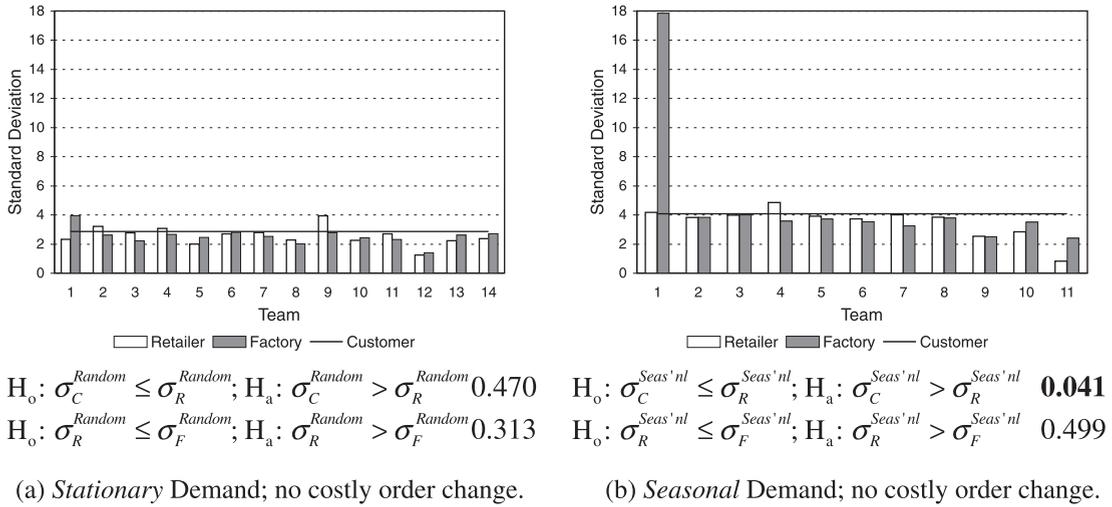


Fig. 2. Demand distributions: order variability in *Short* lead-times treatments with no-costly order changes.

Economic Management and Auctions (LEMA) at Penn State, Smeal College of Business. Participants, mostly undergraduates, were recruited using the on-line recruitment system, with cash the only incentive offered.³ Approximately 50% of our subject pool consists of business majors, 30% are engineering majors, and the rest are in natural and social sciences and humanities. Approximately 60% are male and 40% are female. Based on the individual unit of analysis, we did not find any statistically significant difference in earnings based on these demographics and between retailers and factories.

The experiment proceeds as follows. Participants arrive at LEMA at a pre-specified time and are seated at computer terminals. They take approximately 10 min to study the written instructions (see Appendix I). We then read the instructions to them aloud (to ensure common knowledge of the rules of the game) and answer any questions. Participants complete a brief quiz on the rules of the game, and we go over the answers. After all the quizzes are completed and questions (if any) are answered, participants complete 50 periods of the game. At the conclusion of the sessions, the participants fill out a questionnaire and receive their final payments in private. Average earnings of our experiments were \$20 (about 9500 tokens), and all sessions lasted approximately 60 min.⁴ All sessions were conducted using the Z-Tree experimental economics software program (Fischbacher, 2007).

5. Results

To examine our results, the unit of analysis is the standard deviation of orders: for each participant we compute the standard deviation of orders for the 50 periods in the session.

Because our analysis involves a situation where there are two related samples, we follow Croson and Donohue (2003, 2006) and Siegel (1965, p. 68) and perform nonparametric sign tests. Specifically, to test Hypotheses 1A, 1B, 3A, and 3, we use the matched-pair Wilcoxon test to measure the amount of amplification within a treatment. To test Hypothesis 2, we use the two-sample Wilcoxon test to make comparisons between treatments. When presenting each of our results, we will provide an initial discussion about our findings. In Section 6, we will discuss the implications of our results in more detail.

5.1. Results: demand distributions

We will first examine the results that test Hypotheses 1A, 1B, and 2. To test Hypothesis 1A (in a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution is stationary – does not have a seasonal component) and Hypothesis 1B (in a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution has a seasonal component), we first summarize the standard deviations of orders in the *Stationary* and *Seasonal* short lead time treatments in Fig. 2. All p-values indicating statistically significant differences are in bold. We find that Retailers and Factories do not amplify customer demand variability in either the *Stationary* or *Seasonal* short lead time

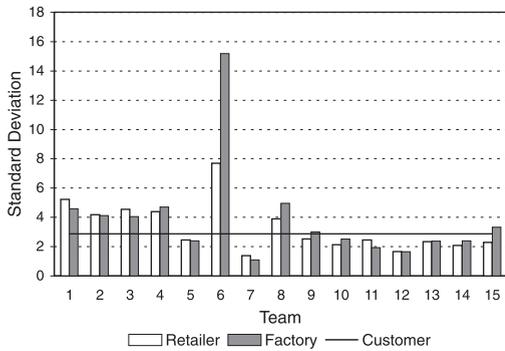
³ Several supply chain laboratory studies are conducted at universities and utilize undergraduate students. Some of these studies show that the decision-making outcomes of students and managers are similar. Using a simulation software program, Holweg and Bicheno (2002) found that there were no significant differences between students and professional managers. Similarly, Croson and Donohue (2006) and Serman (1989) found that there were no differences in the performance among undergraduate, MBA, or PhD students, and senior executives. Finally, Machuca and Barajas (2004) found there were no significant differences in the beer game results between students and executives. Based on this evidence, we do not believe that using students poses a serious problem. Additionally, at the time of the study the beer game was not formally integrated into the undergraduate supply chain curriculum at Penn State.

⁴ We pretested our experiment and discovered that 60 min provided a sufficient amount of time to complete the experiment.

Table 2

Hypothesis testing for the effect of demand distribution (Hypothesis 2). The third row contains median standard deviations of orders in each position. The left-most column states the hypothesis test. The right-most column contains *p*-values (two-sided) from the Wilcoxon test of each hypothesis.

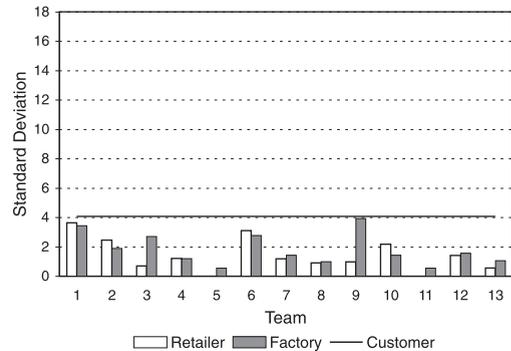
Hypotheses	Stationary demand		Seasonal demand		Wilcoxon <i>p</i> -value
	Retailer	Factory	Retailer	Factory	
Median	2.53	2.57	3.83	3.59	
No costly order change					
$H_0 : \sigma_R^{Random} = \sigma_R^{Seas'nl}; H_a : \sigma_R^{Random} \neq \sigma_R^{Seas'nl}$	X		X		0.008
$H_0 : \sigma_F^{Random} = \sigma_F^{Seas'nl}; H_a : \sigma_F^{Random} \neq \sigma_F^{Seas'nl}$		X		X	0.005



$$H_0 : \sigma_C^{Random} \leq \sigma_R^{Random}; H_a : \sigma_C^{Random} > \sigma_R^{Random} \quad 0.263$$

$$H_0 : \sigma_R^{Random} \leq \sigma_F^{Random}; H_a : \sigma_R^{Random} > \sigma_F^{Random} \quad 0.804$$

(a) Stationary Demand; costly order change.



$$H_0 : \sigma_C^{Seas'nl} \leq \sigma_R^{Seas'nl}; H_a : \sigma_C^{Seas'nl} > \sigma_R^{Seas'nl} \quad \mathbf{0.000}$$

$$H_0 : \sigma_R^{Seas'nl} \leq \sigma_F^{Seas'nl}; H_a : \sigma_R^{Seas'nl} > \sigma_F^{Seas'nl} \quad 0.847$$

(b) Seasonal Demand; costly order change.

Fig. 3. Cost of changing order amount: order variability in Short lead-times treatments.

treatments. In the *Seasonal* treatment, 9 out of the 11 Retailers place orders that are *less* variable than customer demand (Fig. 2), and the median standard deviation of orders for Retailers is below that of customer (*p*-value = 0.041). We also find in the *Stationary* treatment, 11 out of the 14 Retailers place orders that are *less* variable than customer demand. Interestingly, we do not find any evidence of the bullwhip effect or order smoothing among the Factories in either the *Stationary* or *Seasonal* short lead time treatments. Therefore, we find support for *Hypothesis 1A* and *Hypothesis 1B*. These statistical results provide us with evidence that simplifying the supply chain really does minimize the bullwhip effect in the laboratory. We also point out that our findings could provide insight to the important role of vendor-managed inventory systems as a practice that can enable firms to mitigate the bullwhip effect.

To test *Hypothesis 2* (in a two echelon supply chain, when order changes are costless, order variability should be higher in the *Seasonal* demand setting as compared to the *Stationary* demand setting), we will first examine our results in Table 2. As shown in Table 2 in treatments without costly order changes, orders are more variable for both, Retailers and Factories, with *Seasonal* demand than with *Stationary* demand. Therefore, we find support for *Hypothesis 2*. Briefly, the reason for this increase is that *Seasonal* customer demand is substantially more variable than *Stationary*, so even though retailers smooth orders in the *Seasonal* treatment, they do not smooth them sufficiently to make up for the higher variability of customers' orders.

5.2. Results: the cost of changing order amount

We now examine our results that test *Hypothesis 3A* (in a two echelon supply chain, when order changes are costly and the demand setting is *Seasonal*, order smoothing should occur) and *Hypothesis 3B* (in a two echelon supply chain, when order changes are costly and the demand setting is *Stationary*, order smoothing should not occur). We first summarize the standard deviations of orders in the *Stationary* and *Seasonal* short lead time treatments in Fig. 3. As shown in Fig. 3b, when demand is *Seasonal*, the data is consistent with *Hypothesis 3A* because there is strong evidence of order smoothing by the Retailers in the treatment with *Seasonal* demand and costly order changes. Examining Fig. 3a, when demand is *Stationary*, there is no evidence of order smoothing in the treatment with *Stationary* demand and costly order changes.

To test *Hypotheses 3A and 3B*, we first turn to our Wilcoxon tests in Table 3. All *p*-values indicating statistically significant differences are in bold. When the demand is *Seasonal*, there is strong evidence that orders are less variable with costly order changes, consistent with *Hypothesis 3A*. Our results indicate that there is an interaction effect between *Seasonal* demand and

Table 3

Hypothesis testing for the effect of costly order change. The third row contains median standard deviations of orders in each position. The left-most column states the hypothesis test. The right-most column contains p -values (two-sided) from the Wilcoxon test of each hypothesis.

Hypotheses	No costly order change		Costly order change		Wilcoxon p -value
	Retailer	Factory	Retailer	Factory	
<i>Stationary demand</i>					
Median	2.53	2.57	3.27	3.88	
$H_0 : \sigma_R^{None} = \sigma_R^{Costly}; H_a : \sigma_R^{None} \neq \sigma_R^{Costly}$	X		X		0.498
$H_0 : \sigma_F^{None} = \sigma_F^{Costly}; H_a : \sigma_F^{None} \neq \sigma_F^{Costly}$		X		X	0.285
<i>Seasonal demand</i>					
Median	3.83	3.59	1.41	1.81	
$H_0 : \sigma_R^{None} = \sigma_R^{Costly}; H_a : \sigma_R^{None} \neq \sigma_R^{Costly}$	X		X		0.001
$H_0 : \sigma_F^{None} = \sigma_F^{Costly}; H_a : \sigma_F^{None} \neq \sigma_F^{Costly}$		X		X	0.001

Table 4

Summary of hypothesis testing results.

Hypothesis	Finding
Hypothesis 1A: In a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution is known and stationary	Supported
Hypothesis 1B: In a two echelon supply chain, the bullwhip effect will not occur when the customer demand distribution has a seasonal component	Supported
Hypothesis 2: In a two echelon supply chain, when order changes are costless, order variability should be higher in the seasonal demand setting as compared to the stationary demand setting	Supported
Hypothesis 3A: In a two echelon supply chain, when order changes are costly and the demand setting is seasonal, order smoothing should occur	Supported
Hypothesis 3B: In a two echelon supply chain, when order changes are costly and the demand setting is stationary, order smoothing should not occur	Supported

costly order changes that induce order smoothing. Order smoothing that we observe cannot be attributed to costly order changes alone because we do not observe order smoothing in the treatment with *Stationary* demand. When demand is *Stationary*, the data is consistent with **Hypothesis 3B**. Therefore, we find support for both **Hypotheses 3A** and **3B**. A summary of our hypothesis testing results is provided in **Table 4**. These results will be discussed in more detail in Section 6.

6. Discussion

There has been a recent call for greater attention to behavioral issues in logistics and supply chain management (Bendoly et al., 2010; Carter et al., 2007; Croson et al., 2011; Tokar, 2010; Wan and Evers, 2011; among many others). Responding to this call for additional behavioral studies, the purpose of our research is to examine the cognitive reactions of individuals in a behavioral laboratory investigation of production smoothing in supply chains. While past research on production smoothing has been either at an *aggregate* level of analysis (the firm or industry) (e.g., Cachon et al., 2007), in our study, we adopt an *individual* level of analysis on this important topic. Additionally, in contrast to previous laboratory studies of the bullwhip effect (e.g., Machuca and Barajas, 2004), we provide evidence that the bullwhip effect completely disappears in a direct shipment supply chain. To the best of our knowledge, our laboratory study provides the first empirical evidence that when customer demand has a predictable seasonal component, retailers smooth orders. We also found that the smoothing phenomena are more pronounced when changing order levels is costly.

An important contribution of our study is that our results complement prior field examinations of production smoothing including the work of Cachon et al. (2007). Indeed, our laboratory study and the work of Cachon et al. (2007) provide important insight when juxtaposed together (see for example Croson and Donohue, 2002; Colquitt, 2008). Specifically, our research design is motivated in part by Cachon et al. (2007) who identify several structural factors that cause firms to smooth production. Indeed, we examine some of these factors in our laboratory experiment. While some of those factors may be difficult to measure and isolate in the field, especially for individual firms, we designed a set of laboratory experiments that manipulate these factors with a great deal of precision and control. At the same time, the fact that the supply chain attributes we manipulate are factors that have been shown to matter in the field, increases the external validity of our laboratory experiments and also increases the validity of studies on production smoothing, an important contribution of laboratory studies (Cook and Campbell, 1979).

We investigate production smoothing in the context of a simplified supply chain. Our supply chain includes two echelons (the *Retailer* and the *Factory*) instead of the standard four-echelon version commonly found in previous beer game

experiments. We kept the implementation of our supply chain close to the previous beer game literature (see Fig. 1 for the graphical representation of the game in our study). In doing so, we are able to systematically investigate demand and cost factors that affect supply chain performance.

We believe that our simplified two echelon design addresses the cognitive limits of human rationality and decision capability that many previous supply chain laboratory studies have faced. Indeed, a preponderance of previous supply chain laboratory research has found that laboratory participants suffer from cognitive biases and rely on their experience and intuition when making ordering decisions in the beergame (e.g., Croson and Donohue, 2006; Wu and Katok, 2006). Unfortunately in doing so, these laboratory participants deviate from the optimal ordering policy in the beergame and make decisions which result in the bullwhip effect. In contrast to prior studies, we believe that our production smoothing research design presents initial evidence that laboratory participant can engage in desired supply chain behaviors.

Our supply chain laboratory research model and design is based on two factors that Cachon et al. (2007) found to be related to production smoothing in the field: one is the effect of predictable seasonal demand, and the second is the effect of costly order changes. It turned out that our main finding has to do with the *interaction effect* of these two factors. Regular seasonal demand makes it easy for laboratory participants to understand *how* to smooth production. Consequently, Retailers and Factories smooth production in both treatments with *Seasonal* demand, but more so when order changes are costly. We also examined the effect of costly order changes in the *Stationary* treatment. We did not find that Retailers smooth orders when the demand is *Stationary*. Rather, we believe that the production (order) smoothing behavior occurs because our seasonal demand is predictable. Seasonal demand in our study occurs when a value of 0 is always followed by a value of 8 (as opposed to our stationary demand case in which demand in any given period can be any integer value from 0 to 8).

One issue that is sometimes mentioned about beer game experiments in general is that these results are due to the poor understanding of the game by the participants. In other words, if only participants knew the optimal solution, the bullwhip effect would disappear. We would like to point at mounting evidence that the solution is unlikely to be this simple. The setting in Croson et al. (2011) has an optimal solution that is transparent, but participants do not follow it even in the treatment in which this solution is explained to them. Even the most extreme behavior in that study is consistent with a behavioral decision-making heuristic developed by Dogan and Serman (2006). Participants in Wu and Katok (2006) discover on their own a reasonable smoothing ordering policy through experience, in a setting that is significantly more complicated than that in the Croson et al. (2011) study. In fact, in Wu and Katok (2006), when pre-game communication is allowed, some teams decide to implement a smoothing policy instead of a (better) base stock policy. In our study, participants figure out not only how to avoid the bullwhip effect, but also, in a few treatments, how to smooth orders—a task that may be considered more complex, since the bullwhip effect can be eliminated through simply matching orders placed with orders received, but successful order smoothing requires more sophisticated actions.

While our study makes significant contributions to the literature, there are several opportunities for future research. One is to look at the effect of supply chain length. Cachon et al. (2007) find, looking at three levels of field data (retailers, wholesalers, manufacturers), that retailers and manufacturers are more likely to smooth orders, while wholesalers are more likely to amplify the variability. To check whether this regularity holds in the laboratory requires at least a 3-echelon supply chain. Additionally, future research should examine the production smoothing phenomena in a laboratory investigation that consists of four echelons as tested in earlier research such as Croson and Donohue (2003, 2006) in order to compare our results to previous studies. In our paper, we designed the *Seasonal* condition to have a higher value of end-customer demand variability than in the *Stationary* condition. However, conclusions about the predictability and impact of seasonality might not hold up for different parameters. For example, we could have set customer demand to alternate between the value of 2 and 6 instead of 0 and 8. Therefore, the parameter set for seasonal end-customer demand would result in a standard deviation that would have been lower than the standard deviation for what we designated as stationary end-customer demand in this paper. Future research should explore the impact of these or alternative settings to examine the issues of predictability and seasonality as factors which contribute to production smoothing. Another direction for future research is to look at the effect of price variability. Cachon et al. (2007) find evidence that price variability contributes to amplification. They use price variability as a proxy for promotional activity and cost shocks because direct data on the cost of production factors and on promotional activity is not readily available. The laboratory provides an opportunity to test hypotheses about the effect of cost shock and promotional activity directly. Yet a third direction for future research is to look at the effect of demand shocks. Cachon et al. (2007) report that the amount of autocorrelation in demand does not have a significant relationship with the bullwhip effect. They also note that most industries in their sample have negative demand autocorrelation, so field data does not provide an opportunity for a clean test. A demand stream with a positive autocorrelation, however, can be easily implemented in the laboratory.

7. Conclusion

The purpose of our paper is the behavioral investigation of production smoothing in supply chains. We examine the cognitive reactions of laboratory participants in a two echelon supply chain that consists of a Retailer and a Factory. Because the production smoothing phenomena has been empirically documented at an aggregate level of analysis and scant attention to this issue exists within the controlled setting of the laboratory, we have systematically investigated supply chain features that lead to production smoothing in a laboratory context. In contrast to previous supply chain laboratory studies, we find

that the bullwhip effect disappears in several of our experiments. We show that when customer demand has a predictable seasonal component, retailers smooth orders. This behavior is more pronounced when changing order levels is costly.

The contribution of our paper to the literature is the first creation and empirical testing of a model that examines the cognitive reactions of individuals to the production smoothing phenomena. We respond to the call of Tokar (2010), Wan and Evers (2011), and Carter et al. (2007) for additional behavioral research in the logistics discipline. In so doing, we examine behavioral factors in a logistics model which provides increased insight on how human behavior, judgment, and decision-making affect supply chain performance. Therefore, an important contribution of our research is that we find that laboratory participants are able to overcome cognitive limitations that have been documented in past behavioral studies (e.g., Sterman, 1989; Machuca and Barajas, 2004; Croson and Donohue, 2003, 2006; Croson et al., 2011; Wu and Katok, 2006; Cantor and Macdonald, 2009), and hence respond to the drivers of production smoothing.

In particular, we contribute to the literature by providing strong evidence that individuals in our experiment were able to overcome cognitive limitations to deal with supply chain uncertainty (i.e., perceptions of demand uncertainty, lead-time uncertainty, and trust in their supply chain partner) and thus smoothed orders in response to seasonal demand. We find even stronger evidence of this effect when there are costs to changing orders (i.e., production capacity constraints).

We also build-upon past research and hence contribute to the literature by providing evidence that both field studies and supply chain laboratories of the bullwhip effect and production smoothing can work in tandem. In this study, we provide empirical evidence that compliments prior field research on production smoothing (Cachon et al., 2007). We contribute to the literature by showing how our results enhances the internal validity of prior field studies of the bullwhip effect, such as Cachon et al. (2007). Laboratory and field research can work together to further knowledge about a difficult and complex problem. For example, changing orders may be costly, but these costs can be difficult to measure using secondary data such as US Census data as employed in the Cachon et al. (2007) study.

Our research further contributes to the literature by building-upon past supply chain (bullwhip effect) laboratory studies. Previous supply chain laboratory research has not incorporated important factors that exist in the field (e.g., Croson and Donohue, 2006; Wu and Katok, 2006) including capacity constraints and seasonality demand conditions, as is the case in our study. Thus our study fills a void in the behavioral supply chain literature.

Our research also integrates concepts and contributes to prior vendor-managed inventory (VMI) research (Torres and Matz, 2010; Niranjan et al., 2011; Kaipia et al., 2006; Angulo et al., 2004; Yang et al., 2003). Our study contains elements commonly found in VMI situations including the sharing of point-of-sale (POS) data and the direct shipment of inventory. Therefore, we examine the VMI phenomena by including elements of demand uncertainty and capacity constraints at the *individual* level of analysis. Because we have shown that our simpler supply chain is less cognitively complex than past beer game studies, we call for future research to begin the exploration of the cognitive characteristics of individuals which inhibits their ability to cope with any supply chain complexity.

Appendix A. Beergame instructions

In today's study, you will participate in one game where you will earn money based on your own ordering decisions. If you follow the instructions carefully and make good decisions, you could earn a considerable amount of money. The unit of currency for this session is called a franc.

A.1. Description of the game

You sell "widgets." In this game you order "widgets" over multiple rounds from a supplier. You will find out the demand from your customer before you place an order.

Each of you will participate in teams of two. One of you will be assigned the role of a Retailer; the other will be assigned the role of a Factory.

Your decision is to select an order quantity (or just simply place an order) from your supplier. Orders come from suppliers and are shipped to customers. The Factory's customer is the Retailer. The Retailer's customer is the consumer that is programmed into the computer software.

A sample ordering box is provided below:

The screenshot shows a web-based interface for a retail role in a beergame. At the top, it says "You're role is: **RETAILER**". Below this, several statistics are listed: "Facing a demand of: 8", "You shipped to the customer: 8", "Ending inventory amount: 1", and "You're current amount in backorder: 0". The main part of the interface is a form with the label "Your order amount to the factory:" followed by a text input field. This input field is circled in red, and a red arrow points to it from a separate callout box on the right that contains the text "You enter your order amount here". At the bottom right of the form, there is a red "OK" button.

A.2. Game incentives

If you have unsold “widgets” at the end of a period, called *Overages*, this quantity will be carried over to the beginning of the next period, and the holding cost of each unit in inventory is *0.50 franc*.

If you do not have enough “widgets” to meet your customer’s demand, these units will enter your *Backlog*, which will also be carried over to the beginning of the next period, and the cost of each unit in backlog is *1.00 franc*.

Example: Suppose Starting Inventory is 4, and you received an incoming shipment of 10 units of “widgets.” If the customer demand during this period is 10, then:

Ending Inventory = $4 + 10 - 10 = 4$, and your overage cost is $4 \times 0.50 = 2$ francs.

If customer demand in this period turns out to be 18, then

Ending inventory = $4 + 10 - 18 = -4$. The backlog of four costs $4 \times 1 = 4$ francs.

Ending inventory = $4 + 10 - 18 = -4$. The backlog of 4 costs $4 \times 1 = 4$ francs.

<p>The status of your inventory is provided here.</p>	<table border="1" style="width: 100%; border-collapse: collapse;"> <tr> <td style="padding: 2px;">Inventory at the beginning of this period: 4</td> <td style="padding: 2px;">Incoming Shipment (from factory): 5</td> </tr> <tr> <td style="padding: 2px;">Inventory at the end of this period: 1</td> <td style="padding: 2px;"></td> </tr> <tr> <td style="padding: 2px;">Current amount on backorder: 0</td> <td style="padding: 2px;"></td> </tr> <tr> <td style="padding: 2px;">Total Inventory and Backorder Cost: 2.50</td> <td style="padding: 2px;">Previous Order Amount: 6</td> </tr> <tr> <td style="padding: 2px;">Total Ordering Cost: 1.00</td> <td style="padding: 2px;"></td> </tr> </table>	Inventory at the beginning of this period: 4	Incoming Shipment (from factory): 5	Inventory at the end of this period: 1		Current amount on backorder: 0		Total Inventory and Backorder Cost: 2.50	Previous Order Amount: 6	Total Ordering Cost: 1.00		<p>Incoming shipments are added to your beginning inventory.</p>
Inventory at the beginning of this period: 4	Incoming Shipment (from factory): 5											
Inventory at the end of this period: 1												
Current amount on backorder: 0												
Total Inventory and Backorder Cost: 2.50	Previous Order Amount: 6											
Total Ordering Cost: 1.00												

A.3. Costs

Recall that any inventory that you have on-hand at the end of the period is charged at *0.50 francs* per unit of inventory. Also, any orders that are backlogged is charged *1.00 francs per unit*. This information is available to you as described below.

<p>Total Inventory and Backorder Cost: 2.50</p>	<p>Status of inventory and backorder cost are provided here.</p>
<p>Total Ordering Cost: 1.00</p>	

A.3.1. Ordering costs

Suppose you decide to change the amount of widgets that you want to order from your supplier. If you desire to order an amount that is different from your order quantity in the previous period, then you will be charged a fee to do so. The fee that you are charged depends on the extent of the change in order quantity. At a minimum, you will be charged *0.50 francs* multiplied by the change in order quantity level.

Example: Suppose in Period 1 you ordered 10 widgets from your supplier. In Period 2, you desire to order 30 widgets from your supplier. Then, the ordering cost for changing order quantity level is the following:

Ordering cost: $30 - 10 = 20$. The ordering change fee is: $20 \times 0.50 = 10$ francs.

If you decide to order 10 widgets in Period 2, then there is not any ordering cost.

Ordering cost: $10 - 10 = 0$. The ordering change fee is $0 \times 0.50 = 0$ francs.

If you decide to order 0 widgets in Period 2, then the ordering cost for changing order quantity levels is the following:

Ordering costs: $10 - 0 = 10$. The ordering change fee is $10 \times 0.50 = 5$ francs.

Total Inventory and Backorder Cost:	2.50
Total Ordering Cost:	1.00

Status of order cost is provided here.

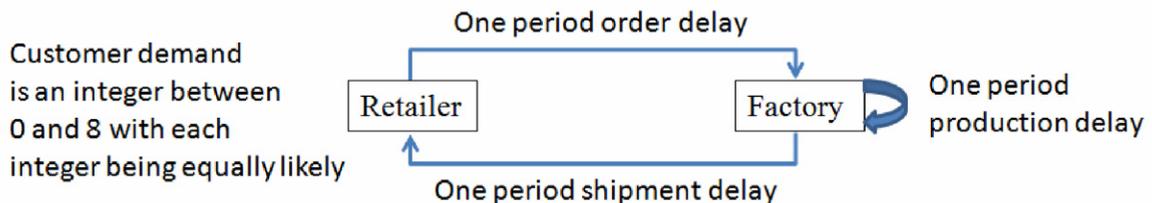
A.4. Delays

A.4.1. Retailer

There is a **1** period delay from the time that the retailer places an order until it arrives to the factory. There is a **2** period delay from the time that the retailer places an order until that shipment is received by the retailer.

A.4.2. Factory

There is a **1** period delay from the time that the factory places the order until it arrives to the factory.



A.5. Customer demand

The retailer's customer demand is an integer from 0 to 8, with each integer from 0 to 8 being equally likely. Demand in one period has no effect on demand in the other period. The customer will demand units of "widgets" from the Retailer. The Retailer will demand units directly from the Factory.

A.6. How you make money

Your decision is to select an order quantity for "widgets." You will make **50** decisions in this game. Starting Inventory is set to four units at the beginning of the game. For the first two periods, your supplier will provide you with four units. You will earn money by making ordering decisions which results in the lowest total supply chain cost for your team. Supply chain cost consists of: total inventory and backorder cost.

A.7. How you will be paid

You will participate in one game, which consists of 50 decisions. Each team is given an *endowment* of 630 tokens at the beginning of the game. All team members' costs will be added together to calculate the total team costs in order to get your final earnings which is based on the below formula:

$$\text{Earnings} = (\text{endowment} - \text{total supply chain costs})/2 * \text{conversion rate} + \text{show-up fee}$$

Both team members will earn the same amount. The lower your team's costs are, the more money you will earn in this game. Thus, your objective is to make ordering decisions that minimize the total costs of your team over the entire game. However, it is possible for a team to go bankrupt during the game. If your team's endowment minus your chain costs becomes negative before the 50 weeks end, your earnings will be **ONLY** the show-up fee.

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