An Investigation of Buyers' Forecast Sharing and Ordering Behavior in a Two-Stage Supply Chain

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Dedication

Dedicated to my parents and my wife

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Abstract

Profitably balancing demand and supply is a continuous challenge for companies under changing market conditions, and the potential benefit of collaboration between supply chain partners cannot be overlooked by any firm who strives to succeed. One of the key elements to successful collaboration is sharing of forecast information between supply chain partners. However, when supply shortage is expected, buyers may inflate order quantities and/or order forecasts to secure sufficient supply. An important question that arises is how the supplier should allocate inventory to customers when shortage exists. Literature shows that certain allocation policies can reduce buyers' order inflation behavior. However, this has not yet been empirically shown for order forecast inflation behavior, nor incorporating the behavioral aspects of decision makers. In this dissertation, through behavioral experiments using a supply chain simulation game, we investigate the impact of different capacity allocation mechanisms and information disclosures of a supplier on buyers' forecast sharing and ordering behavior.

We first investigate the buyers' order forecast sharing behavior in a single-supplier-two-buyer supply chain. Our behavioral study shows that forecast-accuracy based allocation, where the supplier allocates more capacity to the buyer with better forecast accuracy, can significantly improve order forecast accuracy relative to uniform allocation, where the supplier equally allocates capacity to the buyers. Under both policies, particularly uniform allocation, the order forecast accuracy is improved with the supplier's information disclosure on the policy. Next, we focus on buyers' ordering behavior, and formulate a single-supplier-single-buyer base-stock inventory

model under constrained supply. We validate our analytical results through numerical simulation, which is then extended to the single-supplier-two-buyer case. We next compare the buyers' optimal decisions from the simulation with the actual decisions in our behavioral study, and find that buyers in the experiment show a significantly lower profit performance ranging from 0.8% to 14.1%. Using structural estimation modeling techniques, we estimate the buyers' perceived overage/underage cost ratios from the experiment, and conclude by conducting a detailed analysis on the factors that affect buyers' ordering decisions.

In addition to academic contributions, our results provide insights for practitioners to understand buyers' strategic behavior and help with designing capacity allocation strategies.

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Chapter 1

Overview

Many companies continuously strive to improve their value streams to better fulfill their customers' demand as market conditions change. The semiconductor industry, a prototype of the high-tech industry, especially experiences cyclical changes arising from product innovation and technological advancement, as well as changing customer needs. Profitably balancing demand and supply is an ongoing challenge for companies under such circumstances, and the potential benefit of collaboration between supply chain partners could be hardly overlooked by any firm who strives to succeed.

One of the key elements to a successful collaboration is the sharing of forecast information between supply chain partners. Buyers often share their *demand* forecasts (Mishra et al., 2009) and/or *order* forecasts (also referred to as "soft orders") (Cohen et al., 2003) with their supplier. Sharing *demand* forecast information between supply chain partners would benefit the supplier (Mishra et al., 2009), while sharing *order* forecast with the supplier may also result in a reduced order variability and the bullwhip effect, even more than sharing demand forecasts (Chen and Lee, 2009). However, buyers may update their soft orders many times until the firm order date, and due to this "forecast volatility" (Terwiesch et al., 2005), the supplier faces the risk of cancellation or holding costs, while the buyers face the risk of delay costs (Cohen et al., 2003).

In such collaborative efforts, reasonably aligning incentives between supply chain partners is essential; otherwise, each firm would act in its own best interest, and the shared information would not be credible. For example, when supply shortage is expected, buyers tend to inflate their orders to secure sufficient supply (Cachon and Lariviere, 1999a). Moreover, as soft orders reveal the intention of purchase and are usually without any contractual obligation, buyers may also submit inflated order forecasts to the supplier. Recognizing buyers' tendency of forecast inflation, the supplier may discount or even ignore the shared forecasts, which may result in a further forecast inflation behavior from the buyers (Terwiesch et al., 2005). As a result, no credible forecast sharing would exist between the supply chain partners. High-tech and capital-intensive industries, such as semiconductor and aerospace manufacturing, particularly suffer from this (Özer et al., 2011), due to short product life cycles, heavy competition, and the high pressures of price and cost. While semiconductor equipment buyers expect a high degree of responsiveness, the high value and customized nature of such equipment make it risky for the supplier to start production early, or even keep finished goods inventory.

Another important issue is how the supplier should allocate the capacity to each buyer in times of shortage (Krishnan et al., 2007). Cachon and Lariviere (1999a) analytically show that certain allocation mechanisms can induce or reduce buyers' tendency to submit orders higher than optimal or realistic ordering levels to compete for scarce inventory with other buyers. For instance, the *proportional allocation policy*, where the supplier allocates capacity proportional to each buyer's order quantity, is an "order-inflating" mechanism (Cachon and Lariviere, 1999b), while the *uniform allocation policy*, where the supplier equally divides and allocates the available capacity to each buyer, is a "truth-inducing" mechanism in that it mitigates order-inflation behavior. However, the effect of capacity allocation mechanisms on buyers' order-forecast sharing behavior has not yet been investigated in the literature.

In this dissertation, we investigate the impact of different capacity allocation mechanisms on buyers' forecast sharing and ordering behavior. In Chapter 2, we focus on the buyers' order forecast sharing behavior through behavioral experiments using a supply chain simulation game. Theoretical operations management (OM) research assumes that players in the supply chain are fully rational, making optimal decisions toward a certain goal. However, many behavioral OM papers have shown that due to behavioral aspects such as decision biases, the decision makers often make suboptimal decisions, even under a simple single-period newsvendor setting (Schweitzer and Cachon, 2000; Bolton and Katok, 2008). In this research, we investigate the impact of supplier's capacity allocation mechanisms on the order forecast sharing behavior of human buyers in a *multi-period* setting. To collect data for our study, we conducted behavioral experiments by utilizing a computerized supply-chain simulation game. The game is developed in partnership with a large semiconductor manufacturer, and designed to model a two-stage supply chain with realistic features such as inventory/backlog carryover across multiple periods, buyers' competition for the scarce capacity of their supplier, (long) manufacturing lead times, and stochastic consumer demand. In our game setting, the supplier is computerized, while the buyers are played by human subjects. Our behavioral study shows that forecast-accuracy based allocation, where the supplier allocates more capacity to the buyer with better forecast accuracy, can significantly improve order forecast accuracy relative to uniform allocation, where the supplier equally allocates capacity to the buyers. Under both policies, particularly uniform allocation, the order forecast accuracy is improved with the supplier's information disclosure on the policy.

In Chapter 3 of the dissertation, we focus on the buyers' ordering behavior under uniform allocation using a theoretical framework. We characterize a buyer's optimal base stock level in a two-stage supply chain using analytical and numerical simulation approaches. We first present a single-buyer base-stock inventory model with a supplier that provides 100% fill rate and then one that provides less than 100% fill rate. We validate our results through numerical simulation for both uniformly and normally distributed consumer demand. We then utilize a numerical simulation approach for the two-buyer case, where the supplier allocates inventory equally between the two buyers if the orders exceed available inventory, for both uniformly and normally distributed consumer demand.

In Chapter 4, we empirically investigate buyers' ordering decisions when inventory rationing exists, under uniform allocation policy with/without information disclosure from the supplier about the allocation policy. To the best of our knowledge, the impact of uniform allocation mechanism and its information disclosure on buyers' order inflation behavior has not been empirically shown, particularly using a behavioral framework. We first compare the theoretical benchmark results obtained from simulation in Chapter 3 with the observed ordering decisions from our behavioral study. We find that the profit performances of buyers are significantly lower than the theoretical benchmark in the range of 0.8% to 14.1%. Consistent with the findings in the behavioral OM literature (Sterman, 1989), our analysis shows that buyers are prone to make suboptimal ordering decisions, indicating that buyers may not be fully rational. To better understand the nature of buyers' ordering behavior, we use a structural estimation technique to estimate the buyers' perceived cost ratio (i.e., ratio between inventory holding and backlogging costs) and compare it against the true cost parameter ratio. We also investigate what factors affect buyers' ordering decisions and find through maximum likelihood estimation that buyers ignore the supply line regardless of the information disclosure on the allocation policy.

Chapter 5 concludes with a summary of findings, limitations, and future research directions.

Chapter 2

Investigating the Effect of Capacity Allocation Policies on Buyers' Forecast Sharing Behavior in a Two-Stage Supply Chain

2.1 Introduction

One of the key elements of a successful supply chain collaboration scheme is the sharing of forecast information between supply chain partners. In many industries, buyers (who may sell to end consumers or other buyers) often submit forecasts for future orders to their supplier to help with capacity planning. Sharing order forecasts (also referred to as "soft orders") with the supplier can also help with reducing the order variability and the bullwhip effect, even more than sharing demand forecasts (Chen and Lee, 2009). However, buyers may update the soft order multiple times until the firm order is placed, and as a result of this "forecast volatility" (Terwiesch et al., 2005), the supplier takes the risk of cancellation or holding costs, while the buyers take the risk of the delay costs (Cohen et al., 2003). Since soft orders represent the intent of purchasing and are often not legally binding, buyers tend to submit inflated order forecasts to secure capacity from their supplier. The supplier, knowing this forecast inflation behavior of the buyers, may discount or even ignore the forecasts received, leading to lower service levels and longer delivery times, which may further drive the buyers to inflate their forecasts (Terwiesch et al., 2005). The result is virtually no sharing of reliable forecast information between the parties. Capital-intensive industries, such as semiconductor and aerospace manufacturing, particularly suffer from this (Özer et al., 2011). While buyers of semiconductor equipment expect a high degree of responsiveness, the high value and customized nature of such equipment make it risky for the equipment supplier to start production early, or even keep finished goods inventory. Victims of inflated forecasts include the networking giant Cisco Systems who had to write off $2.2 billion worth of inventory in 2001 due to its failure to recognize duplicate orders from its customers (Bloomberg, 2002).

An important issue is how the supplier should allocate his capacity when the total order quantity from buyers exceeds the available capacity (Krishnan et al., 2007). Certain allocation policies can motivate a buyer to submit orders higher than their optimal or realistic levels so as to compete with other buyers for scarce inventory (Cachon and Lariviere, 1999a). For example, in some settings, the *uniform allocation policy*, where the supplier divides the available capacity equally among the buyers, is a "truth-inducing" mechanism, while the *proportional allocation policy*, where the supplier allocates capacity proportional to a buyer's order, is an "order-inflating" mechanism (Cachon and Lariviere, 1999b). The risk of an order-inflating mechanism can be two-fold. First, it may result in uneven allocation of inventory that is far from optimal for the supply chain. Second, the supplier may take the higher-than-usual orders from the buyers as a signal for increasing demand, which could lead to over-building of capacity.

In this chapter, our goal is to understand the endogeneity between a supplier's capacity allocation policy and the buyers' order forecast accuracy. Note that "forecast" refers to the soft orders from buyers in our setting and not the buyers' demand forecasts. Accordingly, "forecast accuracy" refers to the accuracy of the *order forecasts*, i.e., the discrepancy between the soft orders and the firm order. Most theoretical and empirical studies have investigated the effect of capacity allocation policies on order inflation behavior but not the related effect on order forecasting behavior, which is our core research question in this chapter. Krishnan et al. (2007) investigate this question with an empirical study using a large panel dataset of the forecasting and order transactions from a large semiconductor manufacturer and find that when buyers observe a signal of rationing, order forecast volatility ("churn") that the supplier faces increases. Our investigation of this phenomenon is using a behavioral framework. Behavioral operations management (OM) has gained significant interest from researchers over the last decade (Gino and Pisano, 2008). Traditionally, most analytical papers in OM assume that decision makers are fully rational, optimizing decisions toward a single monetary or service-oriented goal. However, as shown by many behavioral OM papers, decision biases may cause individuals to deviate from the optimal, even under a simple setting such as the single period ordering of a newsvendor (e.g., Schweitzer and Cachon, 2000; Bolton and Katok, 2008). Moreover, recent behavioral OM papers have shown that demand forecasting accuracy can be directly impacted by individual differences and judgment biases (Kremer et al., 2011; Moritz et al., 2014; Kremer et al., 2016). In this chapter, we investigate the effect of capacity allocation policies on human behavior for *order* forecasting decisions in a *multi-period* setting, utilizing a computerized simulation game developed in partnership with a large semiconductor manufacturer. The game is designed to model a supply chain with realistic features such as inventory/backlog carryover across multiple periods, buyers competing for the scarce inventory of their supplier, (long) manufacturing lead-times, and stochastic consumer demand.

To understand the effect of capacity allocation on order forecast accuracy, we utilize two policies: (1) We designate the uniform allocation policy (**UNI**) as the control scenario. (2) We propose the "forecast accuracy based allocation policy (**FCT**)," where the supplier allocates (proportionally) more inventory to the buyer with the better order forecast accuracy in case of shortage. Most game theoretical papers on capacity allocation assume that buyers are fully aware of the supplier's allocation policy. However, in practice, suppliers may not entirely disclose their allocation policies to their customers (Krishnan et al., 2007), affecting customers' behavior. We compare buyers' order forecast accuracy under both policies with and without communication from their supplier about the policy.

In summary, our goal is to address the following questions:

1. How do buyers' order forecasting behavior change with the allocation policy of their supplier?

2. Can a forecast-accuracy based allocation policy reduce buyers' order forecast inflation?

3. Does communicating the allocation policy to buyers affect their order forecasting behavior?

It is not straightforward to answer the above questions analytically, and it could be quite costly, or even infeasible, for companies to test the impact of different allocation policies in a real-world setting. Thus, we use the lab environment as a "test bed" to investigate our proposed allocation policy and provide managerial insights. Forecast sharing issues within supply chains have been studied through theoretical and empirical studies, while there are only a few behavioral studies (e.g., Özer et al., 2011; Hyndman et al., 2013; Scheele et al., 2014), which primarily investigate demand forecast sharing. Similarly, capacity allocation policies have been studied theoretically, while behavioral studies are limited and focus on proportional allocation policies with one-shot games (e.g., Chen et al., 2012; Chen and Zhao, 2015; Cui and Zhang, 2017). We contribute to the behavioral OM literature by analyzing the effect of capacity allocation policies on buyers' order forecast accuracy in a *multi-period* setting with *inventory carryover*. We reward better forecast accuracy as in Scheele et al. (2014) but instead of a monetary incentive, we use a more favorable capacity allocation in case of supply shortage. Unlike many existing behavioral OM studies, which test a known or derived theoretical result in the lab, our approach is entirely empirical due to the lack of theoretical results in this complicated practice-driven framework. Thus, our goal is to motivate future analytical and empirical studies in this area while providing insights for practitioners.

Our experimental findings suggest that rewarding forecast accuracy in allocating inventory can lead to improved order forecast accuracy by reducing order forecast inflation and bias. When the supplier communicates this policy to the buyers, even the bullwhip effect may be reduced. While **UNI** has been suggested in analytical studies as a truth-inducing mechanism for orders (Cachon and Lariviere, 1999b), we find that this may not be the case for order forecasts as we observe the highest forecast inflation and error under this setting if there is no communication. Interestingly, **FCT** reduces order forecast inflation compared to **UNI** even without communication.

2.2 Supply Chain Simulation Game Overview

Our game framework is given in Figure 2.1. There is a single supplier (e.g., a computer chip manufacturer) selling a single product to two buyers (e.g., OEMs or distributors). A buyer (she) receives the product from the supplier (he), and sells it to the consumers (possibly after processing and converting it into finished goods). The buyers do not compete in the end market. The supplier has a production lead time, L, that causes a delay between the time that production starts and the time that the product is ready to be shipped to the buyers ($L = 4$ periods in the game). The time it takes to ship the product from the supplier to the buyers and from the buyers to the consumers is short relative to the supplier's production lead time, and assumed to be zero.

The game is played in discrete periods. In each period, buyers place their orders with the supplier and submit forecasts for future orders, while the supplier fulfills received orders (subject to available inventory and allocation policy) and makes production decisions. The forecast horizon (the number of periods into the future for

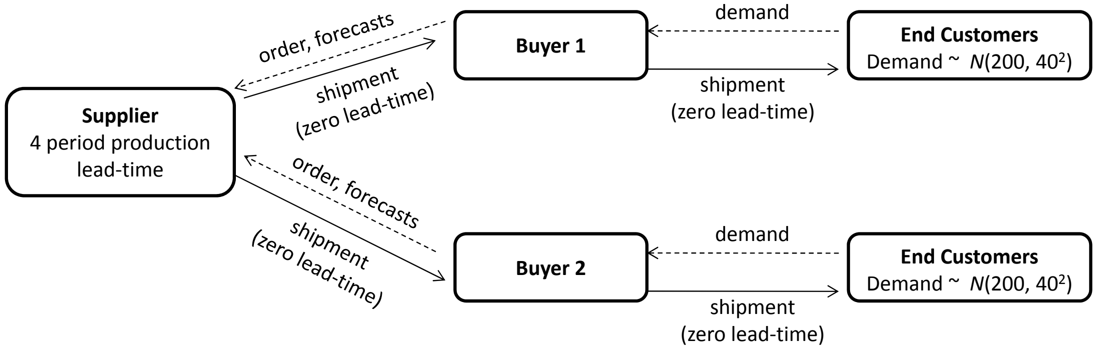


Figure 2.1: Simulation Game Framework

which the buyers provide order forecasts to the supplier) is equal to the production lead time of the supplier. Order forecasts (soft orders) are intended to give the supplier a rough estimate of future orders and can be changed until the firm order is placed. Both the supplier and the buyer have access to the order forecasts and the orders exchanged between the two, so that the order forecast accuracy is common knowledge to both parties. In this game, the role of the supplier is played by the computer with decisions automated through algorithms, while the two buyers are played by human subjects.

The goal for both the supplier and the buyers is to maximize their own profit, which is calculated as the sales revenue from shipping products to one's customers minus the procurement/production cost proportional to the units received/produced and the inventory holding cost or the backlogging cost for unsatisfied demand. Unit selling price and procurement/inventory/backlog cost parameters are chosen according to our semiconductor manufacturer partner's recommendations, and are given in Table 2.1. The consumer demand for both buyers is independent and normally distributed with the same mean and standard deviation ($\sim N(\mu_D, \sigma_D^2)$; $\mu_D = 200$, $\sigma_D = 40$), which is common knowledge to the buyers. Both inventory and backlog units are carried over to the next period.

At the beginning of the game (in period 0), buyers are asked to submit initial order forecasts for the first four periods but there is no order placement. Then, the

Table 2.1: Revenue/Cost Parameters

Parameter	**Supplier**	**Buyers**
Unit Revenue (Selling Price), p	\$1	\$2
Unit Production/Procurement Cost, c	\$0.5	\$1
Unit Inventory Holding Cost, h	\$0.05	\$0.15
Unit Backlogging Cost, b	\$0.15	\$0.45

clock advances to period 1 and in each period, the following events take place (see Figure 2.2):

1. Each buyer submits an order to the supplier asking for a certain number of units to be delivered in that period. Buyers also submit order forecasts for the next four periods.

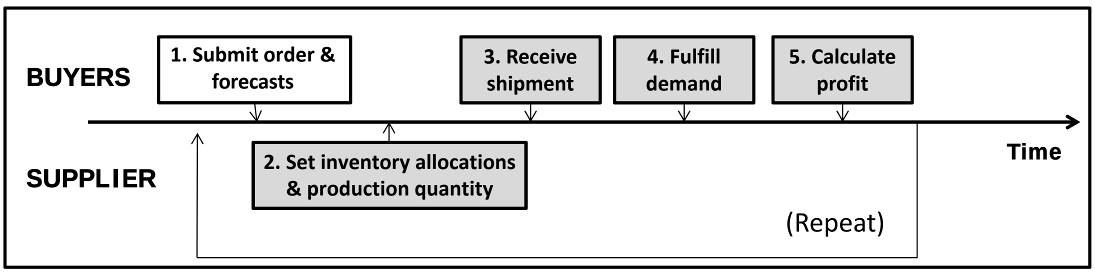
2. The supplier receives the orders and forecasts, and decides on the number of units to be shipped to each buyer and the production quantity for the current period. If he does not have enough inventory to fulfill every buyer's order, some orders will be backlogged and fulfilled in future periods. The backlogged orders are referred to as the "on-order" quantity.

3. Buyers receive the shipments from the supplier immediately, and inventories are replenished.

4. Consumer demand for each buyer occurs, and is filled immediately from inventory. If demand exceeds available inventory, the buyer backlogs the demand and fulfills it in future periods.

5. Profit is calculated for the current period, and the period ends.

The software for the game is coded in C++. It displays various information to help the players with the decision-making process, including performance metrics (e.g., the average per period profit, supplier fill rate and buyer service level, exponentially smoothed forecast accuracy) and system state information (received shipment from the supplier, realized consumer demand in the previous period, on-order quantity, remaining on-hand inventory or backlog carried over from the previous period). We present all game screens with detailed descriptions in Appendix A.5. Note that the service level we refer to for both the supplier and buyers is "*Type 2 Service Level*," or fill rate, i.e., the fraction of demand that is satisfied from inventory, which is commonly used in practice. To differentiate the service level for the supplier and the buyer within the game, we refer to the supplier's service level as fill rate (FL) and the buyer's service level as service level (SL).



Note. All grey boxes are automated within the game.

Figure 2.2: Sequence of Events in Each Period of the Game

Table 2.2 describes the notation for the key variables in this chapter. Next, we describe the supplier's production and allocation algorithms.

2.2.1 Supplier's Production Algorithm

The supplier's production decision in each period is determined by a base-stock policy. After receiving buyers' orders, the supplier chooses a production quantity to raise his inventory position to the target base stock level. The supplier then decides on the shipment quantities, given his finished goods inventory and the inventory allocation policy (see Section 2.2.2). We use a target service level of β for the supplier's base stock level. We assume that backlogs are always satisfied first in a given period. The per period service level is then calculated as $(1 - \frac{B_{it}}{D_{it}})$ for buyer i and $(1 - \frac{\sum_i \mathcal{N}_{it}}{\sum_i O_{it}})$ for the supplier. If the supplier knows that the consumer demand for the buyers per period is i.i.d. normal with $N(\mu_D, \sigma_D^2)$, the expected backorder for the supplier is

Table 2.2: Key Variables

Notation	Definition
D_{it}	Consumer demand realized by buyer i in period t, $i = 1, ..., m$
O_{it}	Order quantity placed by buyer i at the beginning of period t, $i = 1, ..., m$
R_{it}	Received shipment by buyer i in period t, $i = 1, ..., m$
I_{it}:	On-hand inventory of buyer i at the end of period t, $i = 1, ..., m$
B_{it}:	Backlog of buyer i at the end of period t, $i = 1, ..., m$
$\mathcal{N}_{it}$:	On-order quantity that the supplier owes to buyer i at the end of period t, $i = 1, ..., m$
S_{Bi}:	Base stock level of buyer i, $i = 1, ..., m$
F_{itl}	Forecast quantity submitted by buyer i in period t for l periods ahead, $l = 1, ..., L$, $i = 1, ..., m$
π_{it}	Profit of buyer i in period t, $i = 1, ..., m$
IL_t:	Inventory level of the supplier at the beginning of period t
IP_t:	Inventory position of the supplier in period t
S:	Base stock level of the supplier
FGI_t:	Finished goods inventory of the supplier at the end of period t
WIP_{tl}:	Work-in-process inventory of the supplier to be available at the end of period $t + l$, $l = 1...L - 1$
P_t:	Production quantity of the supplier initiated in period t after receiving buyer orders

given by:

$$\mathcal{L}(z) = (1-\beta)\frac{\mu_D \cdot m}{\sigma_D\sqrt{m \cdot L}}$$

where $\mathcal{L}(z)$ is the standard normal loss function, z is the safety factor (safety inventory in terms of the number of standard deviations), and m is the number of buyers. Note that the nominator of the equation is the expected demand in one period only, while the denominator is the standard deviation of demand over lead-time.[1] The base stock level for the supplier is then given by $S = \mu_D \cdot m \cdot L + z \cdot \sigma_D \cdot \sqrt{m \cdot L}$. Let inventory level ($IL_t$) denote the on-hand inventory minus the backorders at the beginning of a period. The inventory position (IP_t) is given by the inventory level plus the on-order inventory, while the amount of production needed (following the base stock policy) is ($[x]^+ = \max\{0, x\}$):

$$P_t = [S - (IP_t - \sum_i O_{it})]^+$$
$$\text{where } IP_t = IL_t + \sum_l WIP_{t-1,l} \qquad \text{and} \qquad IL_t = FGI_{t-1} - \sum_i \mathcal{N}_{i,t-1}$$

At the end of period t, after shipments are sent to the buyers, the inventory components are updated as:

$$FGI_t = (FGI_{t-1} - \sum_i R_{it}) + WIP_{t-1,1}; \qquad WIP_{t,l-1} = WIP_{t-1,l}, \text{ for } l = 2,3$$
$$WIP_{t,3} = P_t; \qquad \mathcal{N}_{i,t} = \max\{\mathcal{N}_{i,t-1} + O_{it} - R_{it}, 0\}, \text{ for } i = 1,2$$

Using a target service level of $\beta = 85\%$ in the game, we obtain the base stock level as $S = 200 \cdot 2 \cdot 4 + (-0.24) \cdot 40 \cdot \sqrt{2 \cdot 4}$=1572. In a preliminary study, we tested low, medium, and high service levels, and found the highest order forecast inflation in the "medium" service level setting. When the service level is too high or too low, the supplier either consistently delivers orders without any delay or consistently carries a backlog. In either case, buyers learn what to expect from the supplier quickly.

[1] For a detailed explanation, see *Cachon, G.P., C. Terwiesch. 2013. Matching supply with demand: An introduction to operations management. McGraw-Hill, New York, NY*

However, when the supplier's service level is medium, his ability to fulfill orders is not consistent, which motivate buyers for strategic behavior. Therefore, we conducted all experiments in this study using the medium service level.

To initialize the system with starting inventory so that the buyers do not have to wait for $L = 4$ periods until the first production batch is available for meeting their orders, we use: $FGI_0 = 454$, $WIP_{01} = WIP_{02} = WIP_{03} = 390$. These values help the system start with a higher service level than implied by the base stock level so as to avoid the cumulative effects of initial inventory shortages on the rest of the game. In particular, a base stock policy could have been optimal for the buyers in the absence of inventory rationing (a buyer's order is not guaranteed to be fully met under a capacity allocation policy). Let S_B denote the base stock level for the buyers. Note that buyers need to make a decision before consumer demand is realized. Thus, in period 1, before any demand realizations are observed, we would expect a "rational" buyer to set her base stock level according to the target in-stock probability given by the critical ratio of the newsvendor model: $P(Demand \leq S_B) = \frac{b}{h+b}$. From Table 2.1, the critical ratio for buyers is 75%, which corresponds to a safety factor of 0.674 from the standard normal distribution, and a base stock level of $200 + 40 \cdot 0.674 \simeq 227$.[2] Thus, rather than equally distributing the supplier's base stock level over four periods of lead-time, we use a higher initial on-hand inventory of $(2) \cdot (227) = 454$, which corresponds to the sum of the buyers' optimal inventory positions in period 1. This ensures that if buyers select their initial orders according to the target in-stock probability defined above, the supplier can fully meet these orders without any backlog. Supplier's inventory position in period 1 then becomes 1624, which implies $P_1 = \sum_i O_{i1} - (1624 - 1572)$ and $P_t = \sum_i O_{it}$ for $t = 2, ..., T$. That is, the production quantity is equal to the sum of orders in each period after period 1. This is limited by the maximum production

[2]Since a buyer receives an order (constrained by the supplier's available inventory) within the same period before demand is realized, we use a lead-time of one for the buyer.

quantity allowed, which is set to 1000 in the game.

Note that the supplier's base stock level is independent of the order forecasts submitted by the buyers in each period. While buyers may submit these forecasts to help the supplier with capacity planning, we are interested in learning the relationship between capacity allocation and order forecast accuracy. If both capacity allocation and production were dependent on the forecasts submitted by the buyers, it would be hard to understand whether the buyer behavior was a result of the supplier's production policy or allocation policy. Moreover, in practice, knowing the tendency of the buyer to inflate forecasts, the supplier may ignore the forecasts received for planning production (Terwiesch et al., 2005). Thus, we make only the allocation policy (in case of **FCT**) to be dependent on forecasts, and assume that the supplier has knowledge of the consumer demand distribution for setting his base stock level.

2.2.2 Supplier's Allocation Algorithms

In a given period, after the supplier decides on the production quantity, he makes a decision on the amount to ship to each buyer. If the buyers' total order amount is less than the available finished goods inventory, the supplier fully satisfies both orders. Otherwise, he chooses the shipment quantity for each buyer based on the implemented allocation policy. The general algorithm for allocation policies is given below (we drop the t subscript from the variables, since this algorithm is executed for every t). Given the available supply at the beginning of period t (FGI_{t-1}), the set of buyers (M), and the orders submitted by the buyers ($O_{it}, i = 1, ..., m$), the supplier allocates inventory such that no buyer is given more than what they asked for ($R_{it} \leq O_{it}$) and no inventory is left unless every buyer's order is fulfilled, while considering each buyer's "worthiness" to claim the inventory ($score_i$), which depends on the type of policy. Note that if there is any outstanding backlog to either of the buyers, this algorithm is first executed for the backlogs, replacing O_i with $\mathcal{N}_i$. After all backlogs are cleared, the algorithm is executed for the current period orders if there is any inventory left, replacing FGI with $FGI - \sum_i \mathcal{N}_i$. The total shipment to each buyer is then the sum of the two output quantities.

Algorithm 1 General Algorithm for Allocation Policies

Input: Order (O_i) and worthiness ($score_i$) of each buyer ($i \in M$); available supply (FGI)
Output: Shipment quantity to each buyer ($R_i, i \in M$)
Initialization: Set $C \leftarrow FGI$; $o_i \leftarrow O_i$; $M' \leftarrow M$; $R_i \leftarrow 0$
while $C > 0$ and M' not empty **do**
  Set $totalship \leftarrow 0$
  for $i \in M'$ **do**
    Compute allocation of buyer i: $a_i \leftarrow C \cdot \frac{score_i}{\sum\limits_{j \in M'} score_j}$
    Assign $R_i \leftarrow R_i + \min\{a_i, o_i\}$ to buyer i
    Set $totalship \leftarrow totalship + R_i$
    Compute the remaining demand for buyer i: $o_i \leftarrow o_i - R_i$
    if $o_i = 0$ **then**
      Remove buyer i from set M': $M' \leftarrow M' \setminus i$.
    end if
  end for
  Update the remaining inventory: $C \leftarrow C - totalship$
end while

We calculate $score_i$, which depends on the type of allocation policy, as follows:

(i) **Uniform Allocation Policy (UNI):** The supplier equally distributes available inventory among buyers with positive remaining demand.

$$score_i = 1 \quad \text{for } i = 1, ..., m$$

(ii) **Forecast Accuracy Based Allocation Policy (FCT):** The supplier weights each order by the buyer's exponentially smoothed forecast accuracy (FA_{it}) and proportionately distributes available inventory among buyers with positive remaining demand.

$$score_{it} = FA_{it} \cdot O_{it} \quad \text{for } i = 1, ..., m$$

Forecast accuracy is based on the discrepancy between the firm order the buyer places for a given period (O_{it}) and the forecasts (soft orders) she submits prior to the firm order ($F_{i,t-l,l},\ l = 1, ..., L$). We calculate the forecast accuracy as one minus the absolute forecast error divided by the larger of the order or forecast, to keep the metric between 0 and 1 and balance the amount of under- and over-forecasting. Let fa_{it} be the forecast accuracy of buyer i in period t, exponentially smoothed based on the forecasts submitted for period t (t forecasts to be submitted until $t = L - 1$, and L forecasts after $t = L$). The overall forecast accuracy for buyer i (FA_{it}) as of period t is:

$$FA_{it} \leftarrow \alpha \cdot fa_{i1} + (1 - \alpha) \cdot fa_{i0} \quad \text{for } t = 1$$

$$FA_{it} \leftarrow \alpha \cdot fa_{it} + (1 - \alpha) \cdot FA_{i,t-1} \quad \text{for } t = 2, ..., T$$

Thus, we calculate the per period forecast accuracy, fa_{it}, by exponentially smoothing the accuracy across lead-time, and the overall forecast accuracy, FA_{it}, by exponentially smoothing the per period forecast accuracy across periods. We use the same smoothing constant, $\alpha = 0.3$, for both types of smoothing in the game. We set the initial forecast accuracy of buyers to $f_{i0} = 1$, assuming that each player is an honest forecaster at the beginning of the game. To calculate the per period forecast accuracy, we construct a smoothing weight matrix $\mathbf{W}$, where row $j \in \{1, 2, 3\}$ represents the weight vector $\mathbf{W}_j$ for period $t = j$, and row $j = 4$ represents $t \geq 4$. W_{jk} refers to the element in row j and column k of the matrix:

$$\mathbf{W} = \begin{pmatrix} \alpha & & & \\ (1-\alpha)\alpha & \alpha & & \\ (1-\alpha)^2\alpha & (1-\alpha)\alpha & \alpha & \\ (1-\alpha)^3\alpha & (1-\alpha)^2\alpha & (1-\alpha)\alpha & \alpha \end{pmatrix}$$

The forecast accuracy of each individual forecast, $fal_{i,t,t-l}$ is calculated as:

$$fal_{i,t,t-l} = 1 - \left(\frac{[F_{i,t-l,l} - O_{it}]^+}{F_{i,t-l,l}} + \frac{[O_{it} - F_{i,t-l,l}]^+}{O_{it}} \right) \quad l = 1, ..., 4;\ t = 1, ..., T;\ l \leq t$$

where $[x]^+ = \max\{0, x\}$. We then construct the accuracy vector $\mathbf{FAL}_{it}$ for buyer i in period t as follows:

$$\mathbf{FAL}_{it} = \begin{cases} \begin{pmatrix} fal_{i,t,t-1} \end{pmatrix} & \text{for } t = 1 \\ \begin{pmatrix} fal_{i,t,t-2} & fal_{i,t,t-1} \end{pmatrix} & \text{for } t = 2 \\ \begin{pmatrix} fal_{i,t,t-3} & fal_{i,t,t-2} & fal_{i,t,t-1} \end{pmatrix} & \text{for } t = 3 \\ \begin{pmatrix} fal_{i,t,t-4} & fal_{i,t,t-3} & fal_{i,t,t-2} & fal_{i,t,t-1} \end{pmatrix} & \text{for } t \geq 4 \end{cases}$$

Thus, we obtain fa_{it} as:

$$fa_{it} = \begin{cases} \dfrac{\mathbf{W}_t \cdot \mathbf{FAL}_{it}^T}{\sum_k W_{tk}} & \text{for } t = 1, 2, 3 \\ \\ \dfrac{\mathbf{W}_4 \cdot \mathbf{FAL}_{it}^T}{\sum_k W_{4k}} & \text{for } t \geq 4 \end{cases}$$

A proportional allocation policy may encourage order inflation from buyers to secure capacity (Cachon and Lariviere, 1999a,b), and can be expected to have a similar effect on order forecasts. Although the mechanism is proportional in principle under **FCT**, when the two buyers' forecast accuracies differ, then the better forecaster will be rewarded with a higher service level from the supplier. Thus, our expectation with this policy is that it should alleviate the order forecast inflation behavior and motivate the buyers to improve their forecast accuracy. Since the supplier uses a base-stock production policy in our setting, an improvement in the buyers' forecast accuracy will not improve the supplier's overall service level, i.e., if both buyers improve their forecast accuracy to the same level, neither of them will gain an advantage (**FCT** will then be equivalent to a classical proportional allocation policy).

We can see the implications of the allocation policy on supplier's service levels with an example in Table 2.3. In this example, the supplier has a supply of 200 units ($FGI = 200$). Buyer 1 submits an order of 100 units (low type) and Buyer 2 submits an order of 150 units (high type). Since both orders cannot be fully satisfied given the available inventory, the chosen allocation policy and the forecast accuracy of each buyer in case of **FCT** will affect how many units each buyer receives. Under **UNI**, each buyer gets an equal allocation of inventory, so while Buyer 1 observes 100% fill rate, Buyer 2 observes 67%. If the supplier switches to **FCT** and both buyers have 100% forecast accuracy (Case I), inventory is distributed in proportion to the orders placed, which benefits the high type buyer. Namely, the fill rate to Buyer 1 drops to 80%, while that to Buyer 2 increases to 80%. However, if Buyer 1 has better forecast accuracy (Case II), the fill rate to Buyer 1 increases to 90% while that to Buyer 2 decreases to 73%. On the other hand, if the low type buyer also has the worse forecast accuracy (Case III), the penalty in service level is even worse, especially compared to **UNI**. Note that this example reflects the calculations in one period only. While $score_i$ will stay constant for **UNI** across all periods, it will change for **FCT** since FA_i is updated in each period.

Table 2.3: Allocation Policy Example

	UNI		**FCT**					
			I		II		III	
	Buyer 1	Buyer 2	Buyer 1	Buyer 2	Buyer 1	Buyer 2	Buyer 1	Buyer 2
O_i	100	150	100	150	100	150	100	150
FA_i	-	-	1	1	1	0.8	0.8	1
$score_i$	0.5	0.5	0.4	0.6	0.45	0.55	0.35	0.65
R_i	100	100	80	120	90	110	70	130
$\mathcal{N}_i$	0	50	20	30	10	40	30	20
$fill\_rate_i$	100%	67%	80%	80%	90%	73%	70%	87%

2.3 Literature Review and Hypothesis Development

We refer the reader to Bendoly et al. (2006) and Katok (2011) for comprehensive reviews on behavioral studies in OM. This chapter falls under three broad streams of research: Forecast sharing, capacity allocation and the bullwhip effect. We next review the papers in each stream and introduce our hypotheses.

2.3.1 Forecast Sharing

Forecast sharing has been studied in various contexts. In a one-buyer one-supplier setting, standard game theory dictates that the only Nash equilibrium (NE) in a one-shot game is uninformative, i.e., the buyer does not share her forecast truthfully and the supplier does not use the reported forecast in determining capacity. Most theoretical studies propose contracts and sharing formats to induce truthful *demand* forecast sharing (Cachon and Lariviere, 2001; Özer and Wei, 2006; Mishra et al., 2009; Taylor and Xiao, 2010; Amornpetchkul et al., 2015; Shamir and Shin, 2016; Chen et al., 2016; Jiang et al., 2016). For truthful *order* forecast sharing, Durango-Cohen and Yano (2006, 2011) propose forecast-commitment contracts, which require commitments by both the buyer and supplier to purchase/deliver a certain fraction of the submitted forecasts, while Baruah et al. (2016) propose a soft order revision mechanism for the buyer, where she needs to pay an upfront deposit for the soft order, with or without access to the supplier's inventory position information.

Truthful sharing of *demand* forecasts can emerge as a result of the trust between supply chain partners, which is shown analytically as an equilibrium in an infinitely repeated game by Ren et al. (2010), with behavioral studies by Özer et al. (2011, 2014), and with numerical simulation by Ebrahim-Khanjari et al. (2012). Hyndman et al. (2013) show with a behavioral study that truthful *demand* forecast sharing can help supply chain partners coordinate capacity decisions. They also examine the effect of pre-play communication, and find that even if the information is not fully truthful, communication can act as a coordinating mechanisms and be effective in increasing profits. Their results (focusing on *demand* forecasts) are in line with our findings (focusing on *order* forecasts) in that communication of a supplier's allocation policy to his buyers can effectively improve the forecast accuracy of the buyers. Scheele et al. (2014) add to these findings with a behavioral study that a targeted use of penalties on *demand* forecast inaccuracies, which penalize over-forecasting more than under-forecasting, can further motivate a buyer to share credible forecasts and eliminate forecast distortions.

We contribute to the behavioral OM literature in forecast sharing by analyzing the effect of capacity allocation policies on buyers' *order* forecast accuracy. We reward better forecast accuracy as in Scheele et al. (2014) and Chen et al. (2016) but instead of a monetary incentive/penalty, we propose a more favorable capacity allocation policy (**FCT**) in case of supply shortage. Moreover, all of the above literature employ one-shot or repeated game settings, while we analyze a *multi-period* setting with *inventory carryover* across periods. Theoretical analysis of such a framework is quite difficult; hence, we use the lab environment to draw insights into the effectiveness of the proposed allocation mechanism in reducing order forecast inflation.

In our analysis, we use four metrics to measure order forecast accuracy and understand a buyer's forecasting behavior:

- **Mean Forecast Error**: The positive or negative bias in order forecasts.

$$m\_fe_t := \frac{\sum_{l=1}^{n}(F_{i,t-l,l} - O_{it})}{n}, \qquad n = t \text{ for } t < L; \;\; n = L \text{ for } t \geq L$$

- **Mean Absolute Forecast Error**: The positive and negative order forecast errors weighted equally.

$$ma\_fe_t := \frac{\sum_{l=1}^{n}|F_{i,t-l,l} - O_{it}|}{n}, \qquad n = t \text{ for } t < L; \;\; n = L \text{ for } t \geq L$$

- **Mean Forecast Inflation**: The positive order forecast error.

$$m\_inf_t := \frac{\sum_{l=1}^{n}[F_{i,t-l,l} - O_{it}]^+}{n}, \qquad n = t \text{ for } t < L;\;\; n = L \text{ for } t \geq L$$

- **Base Forecast Inflation**: The percent forecast inflation with respect to the mean consumer demand (μ_D).

$$base\_inf_t := \left(\frac{\sum_{l=1}^{n} F_{i,t-l,l}}{n} - \mu_D\right)/\mu_D, \qquad n = t \text{ for } t < L;\;\; n = L \text{ for } t \geq L$$

Given that forecasts in our framework refer to soft orders, the first three metrics measure buyers' forecast accuracy with respect to their firm orders. The base inflation metric is used to investigate whether players would submit a forecast different than $\mu_D = 200$. If forecasts are higher than 200, it may indicate that buyers are inflating their forecasts with respect to the consumer demand but not necessarily with respect to the orders they are planning to place. Since buyers face inventory rationing, it is possible to see forecast inflation with respect to both consumer demand and firm orders, potentially at varying levels by allocation policy and communication, which we discuss next.

2.3.2 Capacity Allocation

Capacity allocation decisions are important in any industry where a supplier needs to make an allocation decision when the total demand from his buyers exceeds available inventory. Accordingly, developing effective allocation mechanisms has received considerable attention in theoretical studies, primarily in one-supplier-two-buyer settings. There are four common allocation schemes: proportional, linear, lexicographic and uniform (Cachon and Lariviere, 1999a,b). In "individually responsive" policies such as proportional or linear allocation, a buyer can receive a larger allocation by placing a larger order, which motivates the buyer to act strategically and inflate her order. On the other hand, with uniform allocation or lexicographic allocation (which specifies a sequence in which retailer orders are to be satisfied irrespective of order sizes), truth-telling behavior is shown to be a dominant NE and there is no order inflation. Behavioral studies on capacity allocation focus on proportional allocation mechanisms in one-shot games, and find that NE exaggerates buyers' tendency to strategically order more than they need. Chen et al. (2012) and Chen and Zhao (2015) develop a behavioral model based on the quantal response equilibrium under deterministic and stochastic demand, respectively, while Cui and Zhang (2017) propose a behavioral model based on cognitive hierarchy theory.

We contribute to this literature by investigating allocation policies in a *multi-period* setting with *inventory carryover*. In theoretical studies, uniform allocation has been shown to result in no order inflation unless there is demand competition for the buyers (Liu, 2012; Cho and Tang, 2014). However, this has not been analyzed for its effect on order forecast inflation. Thus, we use **UNI** as our control scenario to investigate whether buyers would have any motivation to inflate their order forecasts under this mechanism. We additionally design a new mechanism (**FCT**), where the supplier "favors" the buyer with the better order forecast accuracy in determining the allocation. Mallik and Harker (2004) and Karabuk and Wu (2005), who study capacity allocation in semiconductor manufacturing, find that proportional allocation can result in truthful forecast sharing with carefully designed bonus payment schemes that reward forecast accuracy. Instead of a monetary incentive, our reward mechanism is directly linked to the allocation policy. Using the lab as a test bed, we compare **FCT** to **UNI** in its effectiveness in inducing truth-telling behavior, which leads to Hypothesis 1:

Hypothesis 1. ***FCT*** *reduces buyers' order forecast inflation and improves order forecast accuracy compared to* ***UNI*** *in a multi-period capacity allocation game.*

For game theoretical analysis, it is typically assumed that buyers have perfect knowledge of their supplier's allocation policy, while in practice, the supplier may not disclose his allocation policy to his buyers (Krishnan et al., 2007), and buyers may make certain assumptions affecting their behavior. We investigate this in an experimental framework, and expect both policies to perform better if the policy is communicated to the buyers (Hypothesis 2(i)). Moreover, a rewarding mechanism can be expected to be more effective in inducing truth-telling behavior if buyers are aware of it. Thus, we expect **FCT** to more significantly improve order forecast accuracy compared to **UNI** when it is implemented with communication (Hypothesis 2(ii)).

Hypothesis 2. *(i) Communication of an allocation policy to the buyers reduces buyers' order forecast inflation and improves order forecast accuracy for both **UNI** and **FCT** in a multi-period capacity allocation game. (ii) **FCT** is more effective in improving buyers' order forecast accuracy compared to **UNI** when it is implemented with communication in a multi-period capacity allocation game.*

2.3.3 Bullwhip Effect

The bullwhip effect refers to the amplification in order variability as one moves upstream in the supply chain from retail to the source of production. Lee et al. (1997b) identify four sources of the bullwhip effect: demand signal processing, inventory rationing, order batching, and price variations. Theoretically, once these operational causes are removed, the bullwhip effect should no longer be observed. However, using the classical beer game, Croson and Donohue (2006) find evidence of the bullwhip effect in lab experiments, even when the demand distribution is shared and all other causes are removed. They attribute this phenomenon to "underweighting the supply line," reported also by Sterman (1989); Niranjan et al. (2011); Bloomfield and Kulp (2013); Croson et al. (2014) and Narayanan and Moritz (2015), where players may not account for the previous orders that have not yet been received from their supplier ("on-order quantity" in this chapter) when placing orders in the next period.

In this study, our primary focus is on buyers' order forecast accuracy, which is a function of the firm orders that they place with the supplier. One might expect that order forecast accuracy may deteriorate if orders are highly variable, or conversely, improving order forecast accuracy can also help with reducing the order variability that the supplier observes. Thus, we investigate the potential bullwhip effect in our setting, which is limited to that of a single echelon as in Bloomfield and Kulp (2013), since the supplier is automated. Unlike previous studies, we consider one of the operational causes of the bullwhip effect: inventory rationing. Even though there is no transit lag (shipment lead-time is zero), a buyer cannot receive her order immediately unless the supplier has enough inventory, which also depends on the other buyer's order quantity. Therefore, we expect the orders to be more variable than demand. However, order variability may be reduced under **FCT** (compared to **UNI**) as buyers may want to keep a more stable order pattern to improve their order forecast accuracy. In particular, when the allocation policy is communicated, the buyers' uncertainty in the supplier's actions would be reduced, and they would need to rely less on "learning by doing".

Hypothesis 3. *The bullwhip effect is reduced under **FCT** compared to **UNI** when it is implemented with communication in a multi-period capacity allocation game.*

2.4 Experimental Design and Results

In this section, we discuss the experimental design to test our hypotheses, and present our results.

2.4.1 Experimental Design

Our research focus is on the effect of the implementation and communication of **FCT** in improving buyers' forecast accuracy. Thus, we use a 2x2 between-subjects design for our experiments (Table 2.4). The first factor represents the implementation of the allocation policy: **UNI** vs. **FCT**. The second factor represents the communication of an allocation policy: no information (**NI**) vs. information (**I**). In the **NI** treatments, we do not disclose any information about how the supplier allocates inventory to his buyers, while in the **I** treatments, we provide the following information to the subjects: Under **UNI**, "*When total order exceeds inventory, supplier will make an equal amount of inventory "available" to each buyer. Each buyer can then receive up to their order amount from the inventory made available to them, and the remaining portion of the inventory will be made available, again equally, to the remaining buyers who still have excess demand, etc. until all the inventory is allocated.*", and under **FCT**, "*When the supplier has tight capacity, he may favor the buyer with higher forecast accuracy in allocating inventory.*" Note that to make the experiments realistic, we provide relatively discreet information about the allocation mechanism, particularly for **FCT**. Thus, the information presented to the subjects is only expected to make them aware of the rewarding mechanism in **FCT**, which may motivate them to improve their forecast accuracy.

The design matrix is given in Table 2.4. Each cell includes the treatment number, and the number of subjects who participated in the treatment (in parentheses, excluding outliers). Our base treatment is **1** while our main treatment of interest is **4**. The comparisons between treatments **1** vs. **2** and **3** vs. **4** help us see the effectiveness of **FCT** relative to **UNI** (Hypothesis 1), while **1** vs. **3** and **2** vs. **4** help us see the impact of communication on the effectiveness of an allocation policy (Hypothesis 2(i)). We also provide cross comparisons of **1** vs. **4** and **2** vs. **3** to further investigate the effectiveness of **FCT** over **UNI** with communication for either policy (Hypothesis 2(ii)).

We recruited student subjects from two major universities in the southeastern U.S.: industrial engineering majors and business students majoring in supply chain management, at undergraduate and graduate levels. A subject was allowed to participate in only one experiment session, and was required to have taken a supply chain

Table 2.4: Experimental Design

	Implementation	
Information	**UNI**	**FCT**
NI	**1** (36)	**2** (40)
I	**3** (40)	**4** (40)

related course prior to the session to qualify. In each session, subjects were randomly assigned to a treatment, and those who were assigned to **I** treatments were provided the information text on a separate piece of paper. Each subject was matched with another randomly selected subject to be sourced from the same supplier and had to play with the same "partner" throughout the game session. The subjects did not know the identity of their partners. We refer to the two subjects that were assigned to the same supplier as a "buyer pair." Accordingly, the number of pairs analyzed in each treatment corresponds to half of the number of subjects given in Table 2.4. While more subjects participated in the game sessions, we removed some of them from the analysis (singles and outliers; see Appendix A.1 for details).

All subjects played the game for 50 periods ($T = 50$) but were not told upfront about the duration of the game so as to avoid end-of-game effects. As the supplier was automated, the game advanced to the next period once both subjects in a buyer pair submitted their orders. Each session lasted about 75-90 minutes. At the beginning of a session, we explained the game context and dynamics to the subjects, as described in Section 2.2, and walked them through the game screens. The buyer's revenue/cost parameters were presented to all subjects; however, supplier parameters were kept private (except for the supplier's selling price, which is the procurement cost for the buyers). We also did not give any specific information about the supplier's production and allocation policies, except for the information described above for the **I** treatments. To ensure that the subjects understood the basics, decision tasks, and metrics displayed on the game screens, we gave a verbal quiz.[3] Only after we received the correct answers and clarified the subjects' questions, we started the session.

To encourage participation and motivate the subjects to play the game with best effort, we offered monetary incentives: a fixed fee of $20 for participation, and an additional reward of up to $10 based on their performance. We calculated this additional reward in proportion to each player's profit such that the player with the lowest profit during the game session received $0, while the player with the highest profit received $10. The payoffs for the remaining players were distributed on this scale in proportion to their profit.

2.4.2 Experimental Results

Our dataset consists of 7800 observations from 156 subjects over 50 periods (see Table 2.4). All statistical analysis is conducted in Stata 14.2. We use the nonparametric Mann-Whitney (MW) test for all statistical comparisons unless otherwise stated.[4]

We first compare the first half of the game (the first 25 periods) with the second half of the game (the last 25 periods) using the descriptive statistics given in Table 2.5. We observe a clear learning effect with higher profits per period, lower backlogs, higher service levels for the buyers and the supplier (supplier's average fill rate gets closer to the target level of 85%), and more stable inventory positions (lower standard deviation) in the second half of the game. As these differences are statistically significant (MW test, $p < 0.001$), we only report the analysis results from the second half of the game, with more stable decisions in a relatively "steady-state" system.[5]

[3]The game screens and the verbal quiz are provided in Appendices A.5 and A.6.

[4]We identified periods with very high/low orders that could bias forecast accuracy metrics. This outlier detection process removed 95 (226) observations from the second (first) half (referred to as "order outliers"). Our robustness checks confirm that including these outliers does not generally change our main results. See Appendix A.1 for details.

[5]See Appendix A.3 for the analysis of the first half of the game.

Table 2.5: Learning Effect over Time

	1st Half			**2nd Half**		
	Mean	*S.D.*	*Median*	*Mean*	*S.D.*	*Median*
Profit (π)	175.0	81.2	182.3	185.7	68.8	190.1
On-hand inventory (I)	40.8	95.4	0	45.7	59.9	21
Backlog (B)	38.8	56.6	13	14.8	28.1	0
Inventory position (IP^b)	276.6	143.0	249	266.3	68.5	251
Order quantity (O)	210.2	48.2	210	199.3	41.6	200
Service level (SL)	83%	24%	94%	93%	13%	100%
Supplier's fill rate (FL)	71%	31%	79%	84%	21%	96%

Note. $N = 3674$ observations in the first half and $N = 3805$ in the second half.
S.D.: Standard Deviation

We next compare treatments to understand the effect of the implementation and communication of a capacity allocation policy on order forecast accuracy. We calculate the average order forecast submitted for each period t as $\bar{F_{it}} = \frac{\sum_{l=1}^{n} F_{i,t-l,l}}{n}$ (for $n = t$ for $t < 4$; $n = 4$ for $t \geq 4$). Descriptive statistics on the order quantity, forecast, and forecast accuracy metrics by treatment are given in Table 2.6. All analysis is conducted at the subject level using the MW test unless otherwise stated.[6] We present the box plots of all forecast accuracy metrics at the subject and pair levels in Figures 2.3 and 2.4, respectively, and by treatment over time in Figure 2.5.

We first observe in Table 2.6 that while order quantities are very similar across treatments and there is no evidence of order inflation, there is significant variation in the submitted order forecasts across subjects within a treatment as well as across treatments. Namely, the mean and median order forecast are highest under treatment **1** and lowest under **4**.[7] In all treatments, we observe that order forecasts are higher than the mean of the consumer demand distribution, 200. In other words, *there is significant base forecast inflation* ($base\_inf$), particularly under treatment **1**. We also

[6]The MW test results for all forecast accuracy metrics can be found in detail in Appendix A.2.

[7]The differences between **1** vs. **2** ($p < 0.1$) and **1** vs. **4** ($p < 0.01$), and **4** vs. **3** ($p < 0.05$) are statistically significant.

observe that order forecasts are generally higher than the order quantities.[8] Using the pooled dataset across all treatments, we confirm that forecasts (soft orders) are not accurate with respect to the firm orders that are placed. Analyzing the average order forecast error by subject closely, we observe over-reporting behavior (forecast inflation) in 83% of the subjects ($m\_fe > 0$, $Mean = 16.7$, $S.D. = 20.9$), and under-reporting behavior in 17% of the subjects ($m\_fe < 0$, $Mean = -8.0$, $S.D. = 10.9$). Thus, the inflation behavior is more persistent with a larger magnitude and higher variability compared to under-reporting.

We next observe that **1** has the highest base and mean forecast inflation among all treatments. Given that the mean order quantity under **1** is 200.9, this observation provides significant evidence that human subjects choose to inflate order forecasts even when there is no clear reason for them to do so. Recall that the supplier follows a base-stock production policy and uniform allocation policy under this treatment. Thus, the submitted forecasts do not have any impact on the supplier's production or allocation policy under treatments **1** and **3**. However, since the subjects do not have this information under **1**, they seem to think that inflating forecasts will be beneficial.

To test Hypothesis 1, we compare **1** vs. **2**, and find that simply changing the capacity allocation policy from uniform allocation (**UNI**) to one that rewards accurate forecasts (**FCT**) reduces order forecast inflation and error significantly.[9] That is, *order forecast inflation and bias are reduced even when* ***FCT*** *is implemented without communication.* Hence, under **2**, despite having the same level of information as under **1**, buyers seem to learn based on their observations/experience over time that more accurate forecasts lead to better service.[10] When the capacity allocation policy

[8]Order forecasts are higher than both 200 and order quantities at $p < 0.001$ using the Wilxocon signed rank test.

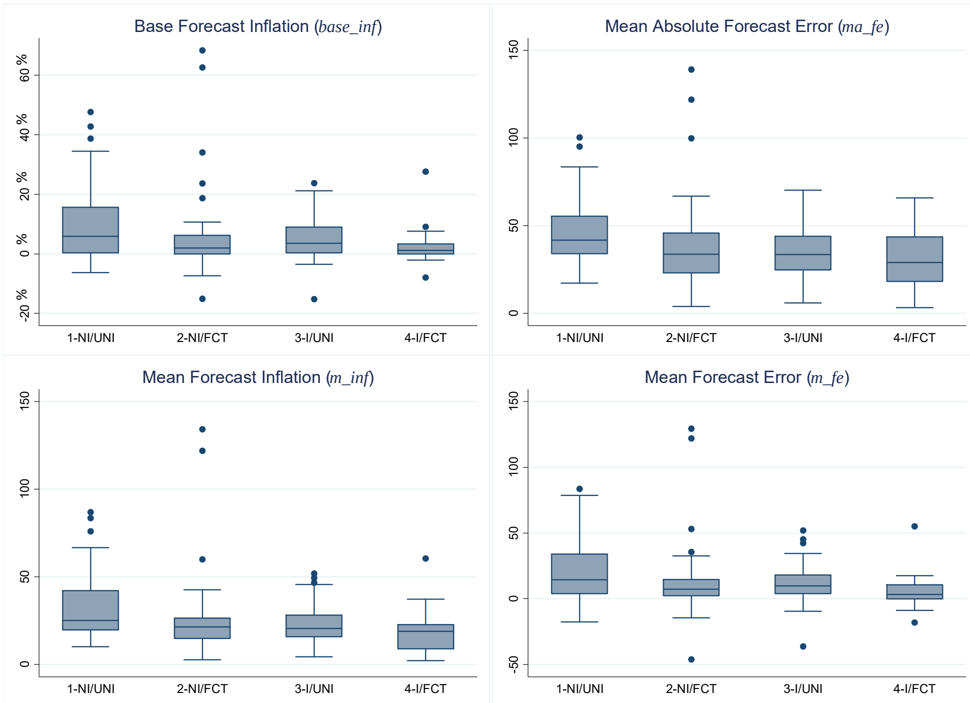
[9]$base\_inf : p = 0.094$; $m\_inf : p = 0.026$; $m\_fe : p = 0.086$.

[10]One subject who played treatment **2** wrote the following feedback to us after the experiment session: "*... the worse my forecast was, the less the supplier seemed willing to fulfill my orders immediately. Once I realized this, I eventually got back to normal by ordering within a range of*

Table 2.6: The Effect of Allocation Policy on Buyers' Order Forecast Accuracy

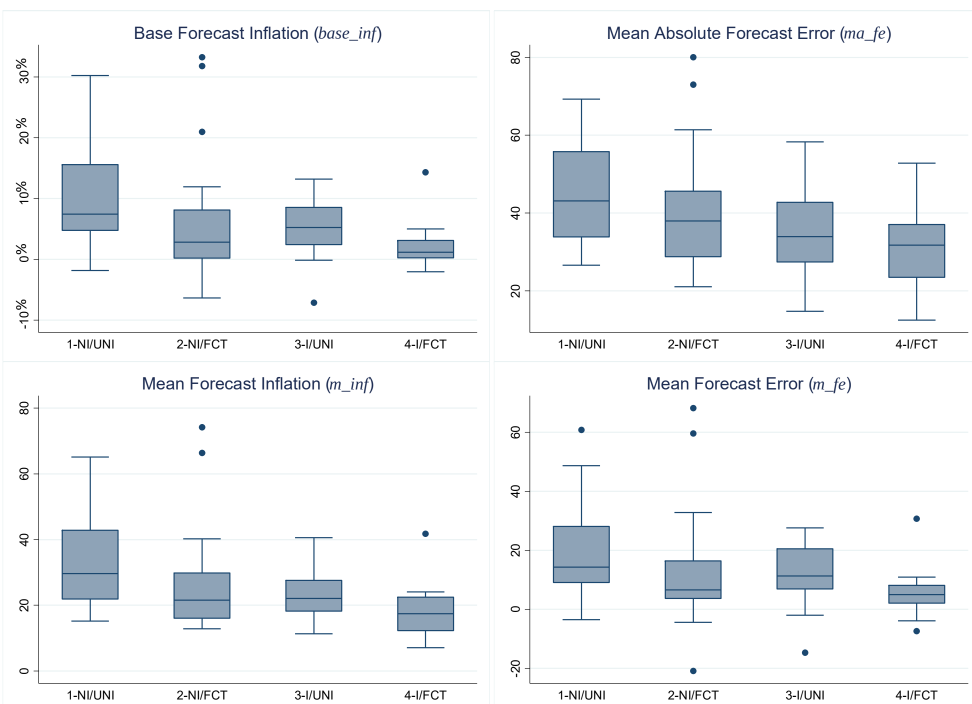
	NI/UNI	NI/FCT	I/UNI	I/FCT
	1	**2**	**3**	**4**
N	36	40	40	40
$\bar{O}$	200.9 (13.4) [198.1]	199.7 (6.7) [199.2]	198.6 (4.8) [199.6]	198.9 (6.6) [199.8]
$\bar{F}$	220.9 (27.2) [211.8]	214.3 (31.2) [204.0]	210.8 (15.2) [207.0]	204.2 (10.0) [202.3]
$base\_inf$	10% (14%) [6%]	7% (16%) [2%]	5% (8%) [4%]	2% (5%) [1%]
m_fe	20.0 (23.6) [14.5]	14.6 (28.7) [7.3]	12.2 (15.6) [9.7]	5.3 (11.1) [3.2]
ma_fe	45.1 (19.9) [41.8]	40.2 (27.5) [32.3]	34.9 (14.7) [33.6]	30.9 (17.1) [29.0]
m_inf	32.6 (19.7) [25.2]	27.4 (26.1) [21.7]	23.5 (11.5) [20.7]	18.1 (11.2) [18.9]

Note. Standard deviations are given in parentheses. Median values are given in brackets. $\bar{O}$ is the average order quantity and $\bar{F}$ is the average order forecast across subjects.



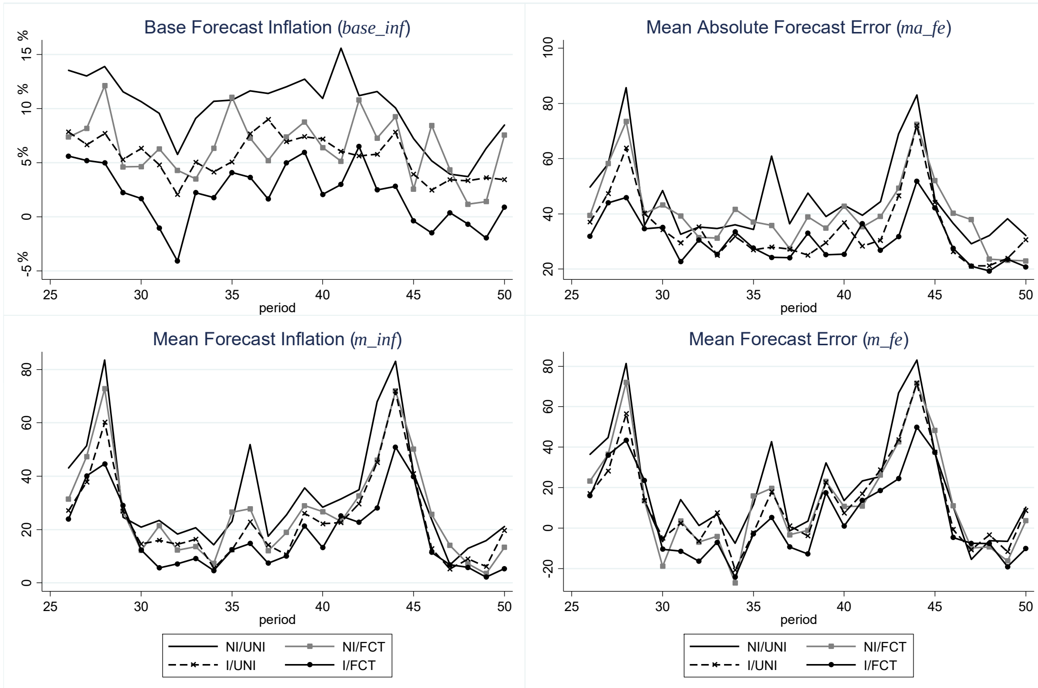
Note. Each plot is based on the average value by subject.

Figure 2.3: Order Forecast Accuracy Metrics by Subject - Treatment



Note. Each plot is based on the average value by pair.

Figure 2.4: Order Forecast Accuracy Metrics by Pair - Treatment



Note. Each data point represents the average value across subjects.

Figure 2.5: Order Forecast Accuracy Metrics over Time by Treatment

is communicated to the buyers, comparing **3** vs. **4**, we find that **FCT** again reduces the order forecast inflation and error compared to **UNI**.[11] While the difference in ma_fe is not statistically significant for either **1** vs. **2** or **3** vs. **4**, Hypothesis 1 is supported in three out of four metrics: ***FCT*** *improves order forecast accuracy by reducing buyers' order forecast inflation and bias compared to* ***UNI***.

To test Hypothesis 2, we first compare **1** vs. **3**, and find that communication of the allocation policy significantly improves order forecast accuracy for **UNI** in two out of four metrics: reducing the mean order forecast inflation and absolute forecast error ($p < 0.05$). This finding supports our previous interpretation of the behavior under **1** that subjects seem to assume that inflating forecasts will be beneficial when they do not have information about what policy the supplier uses. Once they know that

160-240 each period. This gave me a lot of insight about how I and (probably) others tend to act in situations where variability is involved."

[11] $base\_inf : p = 0.019$; $m\_inf : p = 0.059$; $m\_fe : p = 0.005$.

the supplier's allocation is uniform, they no longer seem to find a reason to inflate their forecasts as much. We next compare **2** vs. **4**, and find a similar result (despite a weaker support, $p < 0.1$): communication of the allocation policy improves order forecast accuracy for **FCT** by reducing the mean order forecast inflation and absolute forecast error. Thus, Hypothesis 2(i) is supported in two out of four metrics:[12] *Communication improves order forecast accuracy by reducing buyers' order forecast inflation and absolute forecast error for both allocation policies; however, its effect is more significant for **UNI** than **FCT**.* Communication also does not seem to have a significant effect on the forecast bias (m_fe) for either policy.

Finally, using cross-comparisons, we find that **4** significantly improves order forecast accuracy compared to **1** on all four metrics ($p < 0.01$). Thus, Hypothesis 2(ii) is supported: *When **FCT** is implemented with communication, it effectively improves order forecast accuracy over **UNI** with or without communication by reducing order forecast inflation and bias.* Interestingly, a similar cross-effect does not apply for **UNI**: the difference for **3** vs. **2** is not significant at the subject or pair level for any of the four metrics. Thus, **UNI** *with* communication seems to have a similar performance in order forecast accuracy as **FCT** *without* communication.

In summary, we find that:

- Rewarding forecast accuracy in a proportional allocation policy (**FCT**) can reduce order forecast inflation and bias, compared to a uniform allocation policy (**UNI**), even when the supplier does not communicate his policy to the buyers.

- **UNI** *with* communication can still not provide lower order forecast inflation and bias than **FCT**, even *without* communication. However, communication

[12]For **2** vs. **4**, $m\_inf : p = 0.096$ at the subject and $p = 0.07$ at the pair level, while ma_fe is only significant at the pair level, $p = 0.037$. Although the MW test does not find the $base\_inf$ and m_fe differences significant at the subject or pair level, the unpaired t-test with unequal variances find both differences significant: For **2** vs. **4**, $base\_inf : p = 0.046$ and $m\_fe : p = 0.065$, and for **1** vs. **3**, $base\_inf : p = 0.028$ and $m\_fe : p = 0.05$.

can help reduce order forecast inflation and improve order forecast accuracy under both policies (more significantly for **UNI**).

- **FCT** is most effective in reducing buyers' order forecast inflation and improving order forecast accuracy when it is implemented with communication, providing the most stable (lowest standard deviation) and accurate forecasts.

We next test Hypothesis 3, i.e., the significance of the bullwhip effect, comparing the variability in buyer orders, σ_O^2, to the variability in the consumer demand, σ_D^2. We utilize the nonparametric sign test used in previous studies (Seigel, 1965, p. 68). For each player, we code an increase in the variance of orders placed as a success and a decrease as a failure. If there are no order variance amplifications, we should have $\sigma_O^2 > \sigma_D^2$ at the chance rate of 50%. As seen in Table 2.6, there are no significant differences between the average order quantities across treatments. In Table 2.7, we provide descriptive statistics on the standard deviation of orders and the variance amplification of orders at the subject level. We observe that the mean and median of the standard deviation of orders and the amplification factor for both policies are relatively lower with vs. without communication (**3** and **4** vs. **1** and **2**). Moreover, the sign test shows that the bullwhip effect is statistically significant in all treatments except **4**.[13] In other words, *when **FCT** is implemented with communication, the bullwhip effect is no longer statistically significant.* Thus, we find significant support for Hypothesis 3 as an added benefit of the **FCT** policy, which complements the empirical findings of Chen and Lee (2009)—sharing "truthful" order forecasts with the supplier can also help with reducing the order variability and the bullwhip effect.

To investigate whether subjects underweight the supply line in our setting contributing to the bullwhip effect, we use an approach similar to Croson and Donohue

[13] **1**: $p = 0.002$ with 75% success rate, **2** and **3**: $p = 0.077$ with 63% success rate, **4**: $p = 0.4373$ with 53% success rate. The Wilcoxon signed rank test also fails to reject the null hypothesis $\sigma_O^2 = \sigma_D^2$ for **4** ($p > 0.1$).

(2006) and Niranjan et al. (2011). We run a fixed effects regression model for each treatment, and estimate the subjects' base stock level as a function of previous period's demand, on-hand inventory, backlog, received shipment and on-order quantity (we provide a more detailed analysis on this in Chapter 4). Our results are consistent with the literature: subjects underweight the supply line regardless of the allocation policy (the coefficient for on-order quantity is closer to 0 than -1 in all treatments). However, when we incorporate the average order forecast into the estimation, we find that it has a statistically significant effect (0.321, $p < 0.01$) for treatment **4**, which suggests that subjects take the submitted forecasts into account when placing their orders. This further supports our expectations that when **FCT** is implemented with communication, buyers are motivated to share truthful order forecasts, or equivalently, submit orders in line with their forecasts.

Table 2.7: The Effect of Allocation Policy on Buyers' Order Variability

		σ_O			σ_O^2/σ_D^2		
Treatment	*N*	*Mean*[*Median*]	*Min*	*Max*	*Mean*[*Median*]	*Max*	90^{th}*perc.*
NI/UNI (**1**)	36	44.3 [44.9]	12.56	80.88	1.92 [1.46]	6.73	3.90
NI/FCT (**2**)	40	39.6 [40.1]	11.7	68.2	1.57 [1.37]	5.50	3.09
I/UNI (**3**)	40	37.5 [36.6]	10.4	78.2	1.37 [1.14]	3.94	2.75
I/FCT (**4**)	40	37.4 [36.0]	9.6	64.4	1.48 [1.18]	5.05	3.59

Note. σ_O columns give the mean [median], min and max of the standard deviation of orders at the subject level. The last three columns give the mean [median], max and 90^{th} percentile of the variance amplification factor at the subject level.

2.5 Conclusions

In this chapter, we analyzed the effect of a supplier's capacity allocation policy on the buyers' order forecast accuracy, defined as the difference between the planned (soft) orders and the placed (firm) order, in a multi-period setting with inventory carryover. We proposed a new allocation policy (**FCT**), which allocates limited supply proportionate to the orders but favors the buyer with the better order forecast accuracy. Using the lab environment as a test bed, we compared **FCT** to the uniform allocation policy (**UNI**). We found that under **FCT**, buyers' order forecast accuracy is significantly improved compared to when the supplier uses **UNI**. Thus, our results show that the proportional allocation policy, which is known to motivate order inflating behavior, can be modified to reward order forecast accuracy to dampen order inflation, and consistently reduce order forecast inflation, even when the supplier does not communicate this policy to the buyers.

We also found that communication has a critical role in the effectiveness of an allocation policy. **UNI**, which has been suggested in analytical studies as a truth-inducing mechanism for orders, resulted in the highest order forecast inflation when the supplier did not disclose any information about his policy to the buyers. Under lack of information, buyers seemed to assume that inflating order forecasts could be beneficial in securing supply. Once **UNI** was implemented with communication, there was a significant reduction in the order forecast inflation. **FCT** was also found to be more effective when it was implemented with communication to the buyers. This has an important practical implication as suppliers may not disclose their allocation policies to their customers in real-life (Krishnan et al., 2007). Our results suggest that *if the supplier wants truthful order forecasts from his buyers, then he should openly communicate the allocation policy to the buyers*, similar to the connection between trust and trustworthiness analyzed in Özer et al. (2011). However, we also find that **FCT** improves order forecast accuracy compared to **UNI** even without communication.

Note that since the supplier employs a base-stock production policy in this study, the estimated benefit of **FCT** is conservative. Since the supplier's overall service level to the buyers does not change (significantly) with improved order forecast accuracy, we find that the difference in buyers' average profits across the treatments is not statistically significant. Moreover, buyers' service level to the consumers under **4**

($median$ = 95.6%) is almost identical to that under **3** ($median$ = 95.3%), which are both statistically significantly higher ($p < 0.05$) than that under **2** ($median$ = 92.8%). The service level under **1** ($median$ = 94.0%) is not found to be statistically different than other treatments ($p > 0.1$). We expect that the comparison of profits and service levels between the two allocation policies would lead to additional insights if the supplier's production policy were also a function of the buyers' order forecast accuracy. When that is the case, a buyer may see a tangible improvement in her supplier's service level when she improves her own order forecast accuracy regardless of how the other buyers are forecasting. This may change the order forecasting behavior of the buyers yet again, which is an interesting direction for future research.

With our proposed allocation policy, we show that forecast accuracy can improve even though there are no advance order commitments. This is important in practical settings, such as semiconductor manufacturing, where the forecasts usually represent soft orders without any contractual obligations. Future research could investigate the effect of an order flexibility contract, where the buyers need to commit to a certain percentage of their orders in advance of the firm order date. Such a commitment may motivate the buyers to share truthful forecasts. To the best of our knowledge, this type of contract, also known as the quantity flexibility contract, has not been yet studied through behavioral experiments.

Chapter 3

Characterizing Buyers' Optimal Ordering Decisions in a Two-Stage Supply Chain

3.1 Introduction and Literature Review

In this chapter, we characterize a buyer's ordering decisions in a two-stage supply chain, considering a similar framework as in Chapter 2, using analytical and numerical simulation approaches. We first start with a single buyer-single supplier setting. We assume that there are linear ordering, inventory holding, and backordering costs, but no fixed ordering or setup costs. The buyer in our supply chain uses a base stock policy. Therefore, in each period, she chooses an order quantity to raise her inventory position to her target base stock level. She orders from a single supplier, who also uses a base stock inventory policy, and chooses a production quantity in each period to raise his inventory position to his target base stock level. Consumer demand at the buyer (lowest echelon) is stochastic, independent across periods and stationary. Unmet demand is backlogged at each stage (i.e., there is no lost sales). Since the expected demand per period is constant without any lost sales, the goal of maximizing her total profit is identical to the goal of minimizing her total costs. There is a constant production lead time at the supplier side, while the delivery lead time *from the supplier to the buyer* and *from the buyer to the end-customer* is short relative to the production lead time, thus assumed to be zero. We also analyze two additional two-echelon supply chain settings, where (1) a single supplier serves a single buyer that serves two independent markets; and (2) a single supplier serves two independent buyers (i.e., each buyer serves an independent market). Mathematically, the first one can be considered as a centralized two buyers case, while the latter as a decentralized two buyers case.

There is a rich literature that studies multi-echelon inventory policies since the seminal work of Clark and Scarf (1960). Note that our literature review focuses on multi-echelon inventory systems, where each echelon is allowed to keep inventory, and excludes studies involving a depot-warehouse system, where each depot is not allowed to hold inventory. In typical settings, inventory is managed using either echelon inventory or local inventory. A firm's local inventory position refers to its on-hand inventory plus in-transit and on-order inventory minus backorders, while its echelon inventory position is its local inventory position plus the inventory position of all downstream stages (in the direction of consumer demand). The system optimal solution that minimizes the total average cost per period in such a setting is shown to be an echelon base stock policy (Clark and Scarf, 1960; Federgruen and Zipkin, 1984; Chen and Zheng, 1994). Using a finite horizon model, Clark and Scarf (1960) show that if the upper stream has infinite capacity, the problem can be decomposed into separate single-location problems for each echelon. Thus, the optimal ordering policy can be characterized based purely on echelon inventories. Federgruen and Zipkin (1984) extend their model to infinite horizon under both discounted and average cost criteria, and propose an improved method for optimal policy computations. Chen and Zheng (1994) identify lower bounds on the minimum cost of serial, assembly and one-warehouse-multi-retailer systems by using a cost allocation scheme, and present simpler proofs on the optimality of the policies from the literature. These uncapacitated models are further extended with the inclusion of a production capacity constraint, which may preclude restoring inventories to their base-stock levels in a single period, for a single-stage system in Federgruen and Zipkin (1986a,b), a two-stage system in Parker and Kapuscinski (2004), and a multi-stage system in Glasserman and Tayur (1995). The optimality of a modified base-stock policy under a capacity constraint is shown for the average-cost criterion with discrete demand (Federgruen and Zipkin, 1986a) and the discounted-cost criterion with continuous demand (Federgruen and Zipkin, 1986b), when there is no fixed cost of ordering/setup. While Speck and van der Wal (1991) demonstrate many cases that the modified base-stock policy is not necessarily the optimal policy for periodic review, Parker and Kapuscinski (2004) show that a modified echelon base-stock policy is indeed optimal in a two-stage system, when the downstream capacity is smaller than the upstream capacity. Parker and Kapuscinski (2004) also show that the optimality holds for both stationary and nonstationary stochastic demand cases. Glasserman and Tayur (1995) use a simulation approach to compute derivative estimates for base stock levels in a capacitated multi-echelon system, and show the effectiveness of these estimates in identifying optimal base-stock levels for complex realistic systems. Shang and Song (2003) propose a simple heuristic that reduces a complex N-stage supply chain optimization problem into $2N$ simple newsvendor-type single-stage cost functions, which provide both an upper bound and a lower bound for the echelon cost functions.

While these papers assume centralized policies to optimize total supply chain performance, some studies also consider decentralized decision making, where each stage independently chooses its base stock policy to minimize its own cost (Lee and Whang, 1999; Chen, 1999; Cachon and Zipkin, 1999; Porteus, 2000; JemaÏ and Karaesmen, 2007). Cachon and Zipkin (1999) study both echelon inventory and local inventory tracking regimes and compare the equilibrium between the two regimes. In many decentralized supply chain settings, there is a unique Nash equilibrium, but the Nash equilibrium decisions often deviate from the system optimal decisions (Cachon and Zipkin, 1999). Thus, to align the incentives of the supply chain partners, many studies propose coordination schemes, which are designed in a way that the system optimum can be reached when each firm chooses a policy that minimizes its own cost function.

Examples of such coordination schemes include contracts (Cachon and Zipkin, 1999; Lee and Whang, 1999; Cachon, 2003; JemaÏ and Karaesmen, 2007; Sieke et al., 2012) that allocate costs/benefits to the firms; incentive-compatible measurement schemes such as one based on accounting inventory levels (Chen, 1999)[1]; and responsibility tokens which reimburse the unsatisfied order within the same period (Porteus, 2000)[2]. The common contract types include linear transfer payment contracts (Cachon and Zipkin, 1999; JemaÏ and Karaesmen, 2007), nonlinear transfer payment contracts (Lee and Whang, 1999), and service level contracts (Sieke et al., 2012). Interested readers are referred to Cachon (2003), which provides an overview of the supply chain contracts literature. Our work focuses on the optimal decisions of buyers in a decentralized setting, to particularly understand the behavioral aspects of decision making, and thus we do not propose any coordination schemes.

In setting base stock levels for the buyers and supplier, we use fill rate as a service level metric, which is defined as the fraction of demand/order immediately satisfied from on-hand inventory. The fill rate calculation for periodic review systems is more difficult to characterize and calculate than continuous review systems (Zipkin, 2000). By definition, the fill rate should be computed as the expectation of the ratio of the fulfilled demand in a replenishment cycle to the total demand in a replenishment cycle (Guijarro et al., 2012; Babiloni et al., 2012). However, traditionally the fill rate is computed (approximated) using the ratio of the expected units short per replenishment cycle to the expected total demand per replenishment cycle (Hadley and Whitin, 1963; Johnson et al., 1995; de Kok, 2002). In order for the traditional approach to be accurate, certain conditions, such as (1) *infinite horizon* and (2) *sufficiently large replenishment order to meet existing backorders*, should hold (Chen et al., 2003). The calculation of the expected units short per cycle has been addressed with different

[1]An echelon's accounting inventory level is obtained by an echelon's on-hand inventory minus backorders from the downstream echelon assuming unlimited upstream capacity.

[2]Therefore, every order can be fully served with either actual products or responsibility tokens.

approaches in the literature. Hadley and Whitin (1963) compute it as the difference between the expected total backlog during the replenishment cycle and lead time minus the expected backlog during the lead time, while Johnson et al. (1995) show that this result may result in inaccurate computations especially when the demand variability is high or when the replenishment order is not sufficient to fulfill existing backorders within one period, and propose an alternative fill rate expression. There is a recent stream of papers that focus on exact fill rate computations (Sobel, 2004; Zhang and Zhang, 2007; Teunter, 2009; Silver and Bischak, 2011; Babiloni et al., 2012; Guijarro et al., 2012) in single-stage and/or multi-stage serial supply chain systems. Luo et al. (2014) compare the performance of nine different fill rate expressions through numerical simulations, and show that when the coefficient of variation (CV) is low ($CV < 0.9$), all expressions provide accurate fill rate. Accordingly, since we use a low CV in our behavioral experiments ($CV = 0.2$), we use the traditional fill rate computation in setting our base stock levels.

In addition to the research on fill rate computations, there are also studies on the optimal inventory policies under fill rate constraints in single-stage and multi-stage serial supply chain systems (Boyaci and Gallego, 2001; Axsäter, 2003; Shang and Song, 2006; Sieke et al., 2012). Boyaci and Gallego (2001) investigate the optimal periodic-review echelon base-stock policy, which minimizes average inventory costs of the entire serial production/distribution systems subject to fill-rate constraints at the system level. Thus, their focus is on "how to stock and where to stock under fill-rate type constraints" (Boyaci and Gallego, 2001). In a continuous review serial production/distribution system, Axsäter (2003) show that a multi-stage echelon stock (R, nQ) policy[3] that minimizes holding and backorder costs is optimal. Since exactly meeting the desired fill rate with a pure base-stock policy may be impossible under

[3]Since the model in Axsäter (2003) utilizes a continuous review system, R represents the reorder point, and Q represents the batch size.

discrete demand in practice, applying a combination of multiple base-stock policies, which could achieve the desired fill rate on the average, would be desirable (Boyaci et al., 2003), and as well be optimal (Axsäter, 2003). Shang and Song (2006) provide a closed-form approximation for the optimal base-stock policies in serial supply chain systems. These studies generally concentrate on the system optimal decisions of the supplier that should minimize the inventory holding costs while satisfying the fill rate constraints to the external buyer(s), while our focus is on the optimal ordering decisions of the buyer(s) under less-than-100% target fill rate of the supplier.

Our goal in this chapter is to characterize the buyer's optimal base-stock policy and the associated ordering decisions under a target fill rate from their supplier using an analytical approach for the one-buyer case, which we validate through numerical simulations for both uniformly and normally distributed consumer demand. We then utilize a numerical simulation approach for the two-buyer case, where the supplier allocates inventory equally between the two buyers if the orders exceed available inventory. We use these results in the next chapter to compare against the empirical observations from the lab experiments.

3.2 Analysis of the One-Buyer Case

We derive an optimal inventory policy for a buyer in a two-echelon supply chain, where a single supplier sells a product to a single buyer. The buyer (she) receives the product from the supplier, and sells it to the consumers. The consumer demand is independent and identically distributed across periods, and follows a known stationary distribution with a mean of μ_D and a standard deviation of σ_D. We denote the cumulative distribution function of demand with $F(x)$ (increasing and differentiable) and the probability density function with $f(x)$. Both inventory and backlog units are carried over to the next period. If the supplier does not have enough inventory to fulfill the buyer's order, he backlogs the unsatisfied order and fulfills it in future periods.

The backlogged orders are referred to as the "on-order" quantity. Similarly, if the consumer demand exceeds buyer's available inventory, the buyer backlogs the demand and fulfills it in future periods. We assume that backlogs are always satisfied first in a given period (i.e., before the demand/orders of the current period). This approach ensures that the buyer/supplier does not build up backorders.

Both the supplier and the buyer utilize a (local) base-stock policy. Consistent with Chapter 2, we use *fill rate* as the supplier's service level metric, which denotes the fraction of order/demand satisfied from on-hand inventory. We use a target service level of β for the supplier's base stock level. We first present a single-buyer base-stock inventory model with a supplier that provides *100% fill rate (*$\beta = 1.0$*)* in Section 3.2.1 and less than *100% fill rate (*$\beta < 1.0$*)* in Section 3.2.2.

We provide the key notation used in this chapter in Table 3.1.

Table 3.1: Key Notation

Notation	Definition
S_B	Buyer's base-stock level
p	Unit revenue (selling price)
c	Unit procurement cost
h	Unit inventory holding cost
b	Unit backlogging cost
β	Supplier's target fill-rate to the buyer ($0 < \beta \leq 1$)
D_t	Consumer demand realized by the buyer in period t
O_t	Order quantity placed by the buyer at the beginning of period t
R_t	Received shipment by the buyer at the beginning of period t
$\mathcal{N}_t$	On-order quantity the supplier owes the buyer at the end of period t
IL_t:	Inventory level of the buyer at the beginning of period t
IP_t:	Inventory position of the buyer before placing an order in period t
I_t:	On-hand inventory of buyer i at the end of period t
B_t:	Backlog of buyer i at the end of period t
π_t	Buyer's profit for period t

3.2.1 A One-Buyer Base Stock Inventory Model under 100% Fill-Rate

In this section, we present a single-buyer base-stock inventory model under fully reliable supply (i.e., 100% fill-rate), where the supplier always maintains enough inventory to immediately fulfill the buyer's order from stock.

After the buyer brings her inventory position to her target base stock level, S_B, in period 1, the expected per-period profit over an infinite horizon is calculated as:

$$\begin{aligned} E\left[\pi\left(S_B\right)\right] &= (p-c)\,\mu_D \\ &\quad -h\int_0^{S_B}\left(S_B-x\right)f(x)dx-b\int_{S_B}^{\infty}(x-S_B)f(x)dx \end{aligned} \tag{3.1}$$

First order conditions of the buyer's expected per-period profit gives:

$$\begin{aligned} \frac{\partial E\left[\pi\left(S_B\right)\right]}{\partial S_B}=b-(h+b)\,F(S_B) &= 0 \\ \Rightarrow S_B^* &= F^{-1}\left(\frac{b}{h+b}\right) \end{aligned} \tag{3.2}$$

Second order conditions confirm that the per-period profit function is concave, and thus S_B^* is a global optimal:

$$\frac{\partial^2 E\left[\pi\left(S_B\right)\right]}{\partial^2 S_B}=-\left(h+b\right)f(S_B)<0 \tag{3.3}$$

Thus, over an infinite horizon, the optimal base stock level for a buyer, who is served by a fully reliable supplier, is $S_B^*=F^{-1}\left(\frac{b}{h+b}\right)$, as shown in the literature.

3.2.2 A One-Buyer Base Stock Inventory Model under less-than-100% Fill-Rate

In this section, we present a single-buyer base-stock inventory model under less than 100% reliable supply, where the supplier also uses a base stock policy with a target fill rate of $\beta<1.0$.

After placing an order equal to the base stock level (S_B) in period 1, the buyer would order enough to raise her inventory position (IP_t) back to the target base stock level in period t, where the inventory position at the beginning of period t right before placing an order is given by:

$$IP_t = IL_{t-1} + R_{t-1} + \mathcal{N}_{t-1} - D_{t-1} \qquad \text{for } i = 1, 2;\ t = 2, ..., T \tag{3.4}$$

and $IL_t = I_{t-1} - B_{t-1}$ denotes buyer's inventory level at the beginning of period t. Thus, the order size would be given by the demand of the previous period (D_{t-1}) under a fully reliable supplier. However, since the supplier may not be able to send the order size in full immediately, the buyer's available-to-serve inventory in each period is given by $IL_t + R_t$ or $S_B - \mathcal{N}_t$.

Following Cachon (2003) and Sieke et al. (2012), let S_s be the supplier's base stock level, $D_s > 0$ the demand realized during the supplier's lead-time of L_s, and $F_s(\delta)$ (increasing and differentiable) and $f_s(\delta)$ be the cumulative distribution and density functions of that demand, respectively. Note that as in the previous chapter, we assume that the supplier replenishes according to consumer demand. We also define

$$I_r(S_B) = \int_0^{S_B} (S_B - x)\, f(x)dx, \quad B_r(S_B) = \int_{S_B}^{\infty} (x - S_B) f(x)dx \tag{3.5}$$

We now derive the buyer's expected per period cost over an infinite horizon as:

$$\begin{aligned} E\left[\pi\left(S_B, S_s\right)\right] \;&=\; (p-c)\,\mu_D \\ &\quad -h\left[F_s(S_s)I_r(S_B) - \int_{S_s}^{\infty} I_r(S_B + S_s - \delta)f_s(\delta)d\delta\right] \\ &\quad -b\left[F_s(S_s)B_r(S_B) - \int_{S_s}^{\infty} B_r(S_B + S_s - \delta)f_s(\delta)d\delta\right] \end{aligned} \tag{3.6}$$

Thus, if the supplier can raise the buyer's inventory level to S_B, the buyer's profit function reduces to the fully reliable supplier case, which happens with probability $F_s(S_s)$. Otherwise, the retailer's available inventory level equals $S_B + S_s - x$ (or $S_B - \mathcal{N}_t$).

As it has been shown in Cachon (2003), the optimal base stock level for the buyer will be greater than that for the fully reliable supplier case, i.e., $S_B^* > S_B'$ where

$$F\left(S_B'\right) = \frac{b}{h+b}$$

similar to the 100% fill rate case.

While numerical solution of Equation (3.6) is possible, we demonstrate through simulation that a reasonable approximation for a common demand distribution such as uniform is as follows:

$$F\left(S_B^* - E[\mathcal{N}]\right) = \frac{b}{h+b} \tag{3.7}$$

where $E[\mathcal{N}] = (1-\beta)\mu_D$. Thus, as the buyer's expected order quantity over the long term equals the expected consumer demand (based on an infinite horizon setting with full back-ordering of unmet orders/demand), the supplier would be able to fulfill β of the order immediately, and the expected on-order quantity would be $(1-\beta)\mu_D$ given that he maintains a target service level (fill rate) of β. Thus, the buyer's target base stock level would be increased by the expected on-order quantity.

We next validate this practical result through numerical simulation.

3.2.3 Numerical Simulation Analysis

In this section, we validate our base-stock inventory model derivations through numerical simulation. For this validation, we compare the heuristic base stock level we calculated from the analytical model with the optimal value obtained from numerical simulation. We use the same parameters for the buyer as in Chapter 2: unit selling price of $p = \$2$, unit procurement cost of $c = \$1$, unit inventory-holding cost of $h = \$0.15$, and unit backlogging cost of $b = \$0.45$.

We use two different scenarios: In the first scenario, the buyer sells a single product to consumers in a single market, where consumer demand in each period is independent and follows a uniform distribution (Scenario 1a) or a normal distribution (Scenario 1b). To provide comparable results with our behavioral study in Chapter 2, we use a uniform distribution ($\sim U\,[131, 269]$) and a normal distribution ($\sim N(\mu_D, \sigma_D^2);\ \mu_D = 200,\ \sigma_D = 40$) that have the same mean and standard deviation ($\mu_D = 200,\ \sigma_D = 40$).

In the second scenario, we extend the simulation to a case where the buyer serves two independent markets, and the demand for each market is independent and identically distributed. Consistent with the first scenario, we use uniformly distributed demand (Scenario 2a) as well as normally distributed demand (Scenario 2b). For Scenario 2a, it is well known that the sum of independent and identical uniform distributions follows an Irwin-Hall distribution (also known as "Uniform Sum Distribution"). As its special case, when a buyer serves two markets with independent and identical uniform demand $U(u_1, u_2)$, the pooled demand follows a symmetric triangular distribution with lower limit $2u_1$, upper limit $2u_2$, and mode $u_1 + u_2$, and its cumulative density function is given by:

$$F(x) = \begin{cases} 0 & x < 2u_1 \\ \frac{(x-2u_1)^2}{2(u_2-u_1)^2} & 2u_1 \leq x \leq u_1 + u_2 \\ 1 - \frac{(2u_2-x)^2}{2(u_2-u_1)^2} & u_1 + u_2 \leq x \leq 2u_2 \\ 1 & x > 2u_2 \end{cases}$$

Next, we look into the supplier side. The supplier uses a base-stock policy, and consistent with Chapter 2, has a 4-period lead time ($L_s = 4$). Since the supplier replenishes according to consumer demand, which follows an independent and identical uniform distribution, the demand during the supplier's lead time also follows an Irwin-Hall distribution. For each buyer scenario, we use four target fill rates from the supplier to the buyer: 80%, 85%, 90%, and 100%. While we allow for unlimited and immediate fulfillment for the 100% fill rate case under both scenarios, we set up appropriate target base-stock levels for the less-than-100% fill rate case. For uniform demand distribution, we compute the target base stock levels using the "Uniform-SumDistribution" function in Mathematica 8. For normal demand distribution, we calculate the target base-stock levels as described in Chapter 2. The results are provided in Table 3.2. We conduct simulations for each scenario and fill rate using these supplier target base-stock levels.

Table 3.2: Supplier Target Base-Stock Levels

	Single Market		Two Markets	
	Scenario 1a	Scenario 1b	Scenario 2a	Scenario 2b
80% Fill Rate	786	786	1611	1542
85% Fill Rate	804	804	1635	1572
90% Fill Rate	828	828	1665	1611

For Scenario 1a, we start with the analytical model for the single buyer case, where consumer demand in each period is independent and follows a uniform distribution (i.e., $D_t \sim U[u_1, u_2]$). Equation (3.7) can be solved as follows:

$$
\begin{aligned}
F\left(S_B^* - E[\mathcal{N}]\right) = \frac{S_B^* - E[\mathcal{N}] - u_1}{u_2 - u_1} &= \frac{b}{h+b} \\
\Rightarrow S_B^* - E[\mathcal{N}] - u_1 &= (u_2 - u_1) \cdot \frac{b}{h+b} \\
S_B^* &= \frac{u_2 b + u_1 h}{h+b} + E[\mathcal{N}] \\
&= \frac{u_2 b + u_1 h}{h+b} + (1-\beta) \cdot \mu_D \\
&= \frac{u_1 h + u_2 b}{h+b} + (1-\beta) \cdot \frac{u_1 + u_2}{2} \qquad (3.8)
\end{aligned}
$$

Thus, for instance, for $D_t \sim U[131, 269]$, $h = 0.15$ and $b = 0.45$, $\beta = 0.85$, the heuristic base-stock level is: $S_B^* = \frac{131(0.15)+269(0.45)}{0.15+0.45} + (1-0.85) \cdot \frac{131+269}{2} = 264.5 \approx 265$. We conduct 100 replications of simulations, and record the optimal base-stock levels for the buyer. The average optimal base-stock levels from numerical simulations for 80%, 85%, 90%, and 100% are 275.85, 263.15, 252.23, 232.61, respectively. We compare these values with the base-stock levels that are calculated from Equation (3.8), which give 274.5, 264.5, 234.5, 240.4, respectively. The results are summarized in Table 3.3. For the 80% and 85% fill rate cases, one sample t-test shows that the values obtained from numerical simulations are not significantly different (at $p = 0.05$ level) from the values calculated from the model. For the 90% and 100% cases, although the null hypotheses are rejected (at $p = 0.05$ level), the simulated values are close to the theoretical results. Considering the difference in analytical and simulation settings[4], our heuristic seems to work well as a good approximation to the optimal base stock levels under the uniform (i.e., a linear) demand distribution.

Table 3.3: Scenario 1a Simulation Results vs. Heuristic Results

	Simulation Results				Heuristic Results
	Mean	Std. Dev.	Count	Std. Err.	S_B^*
80% Fill Rate	275.85	18.62	100	1.86	274.5
85% Fill Rate	263.15	15.20	100	1.52	264.5
90% Fill Rate	252.23	11.21	100	1.12	254.5
100% Fill Rate	232.61	5.48	100	0.55	234.5

For Scenario 1b, we start with the analytical model for the single buyer case, where consumer demand in each period is independent and follows a normal distribution (i.e., $D_t \sim N(\mu_D, \sigma_D^2)$). Equation (3.7) can be solved as follows:

$$\begin{aligned} S_B^* - E[N] &= F^{-1}\left[\frac{b}{h+b}\right] \\ \Rightarrow S_B^* &= F^{-1}\left[\frac{b}{h+b}\right] + E[N] \\ &= F^{-1}\left[\frac{b}{h+b}\right] + (1-\beta)\cdot\mu_D \end{aligned} \tag{3.9}$$

For instance, for $D_t \sim N(200, 40^2)$, $h = 0.15$ and $b = 0.45$, $\beta = 0.85$, the heuristic base-stock level from Equation (3.9) is: $S_B^* = F^{-1}\left[\frac{0.45}{0.45+0.15}\right] + (1-0.85)\cdot 200 = 256.98 \approx 257$. For numerical simulations, we conduct 100 replications, and record the optimal base-stock levels for the buyer. The average optimal base-stock levels from numerical simulations for 80%, 85%, 90%, and 100% are 277.92, 264.15, 250.56, 226.29, respectively. We compare these values with the base-stock levels that are calculated from Equation (3.9), which give 266.98, 256.98, 246.98, 226.98, respectively. The results are summarized in Table 3.4. Except for the 100% fill rate case, one sample t-test shows that the values obtained from numerical simulations are significantly

[4]Our heuristic is based on an infinite horizon, while the simulation is based on a finite horizon. The heuristic also does not take the supplier's lead-time into account, while the simulation does.

different (at $p = 0.05$ level) from the values calculated from the model, showing that our heuristic may be underestimating the optimal base stock levels under the normal (i.e., a non-linear) demand distribution.

Table 3.4: Scenario 1b Simulation Results vs. Heuristic Results

	Simulation Results				Heuristic Results
	Mean	Std. Dev.	Count	Std. Err.	S_B^*
80% Fill Rate	277.92	21.44	100	2.14	266.98
85% Fill Rate	264.15	18.18	100	1.82	256.98
90% Fill Rate	250.56	14.23	100	1.42	246.98
100% Fill Rate	226.29	6.03	100	0.60	226.98

For Scenario 2a, we conduct 100 replications of simulations, and obtain the optimal buyer base-stock levels. The average optimal base-stock levels from numerical simulations for 80%, 85%, 90%, and 100% are 483.2, 472.54, 461.27, 438.94, respectively. Then, through Mathematica calculations, we obtain the heuristic base-stock levels for the four fill rates using the pooled demand that follows a symmetric triangular distribution shown above. From Equation (3.7), the pooled base-stock levels are calculated as 480.75, 470.60, 460.50, 440.42, respectively. The results are shown in Table 3.5. The one sample t-test shows that the values obtained from numerical simulations are not significantly different (at $p = 0.05$ level) from the values calculated from the model, validating our analytical results under the uniform distribution.

Table 3.5: Scenario 2a Simulation Results vs. Heuristic Results

	Simulation Results				Heuristic Results
	Mean	Std. Dev.	Count	Std. Err.	S_B^*
80% Fill Rate	483.20	15.51	100	1.55	480.75
85% Fill Rate	472.54	15.82	100	1.58	470.60
90% Fill Rate	461.27	13.32	100	1.33	460.50
100% Fill Rate	438.94	8.40	100	0.84	440.42

For Scenario 2b, we also conduct 100 replications of simulations, and obtain the optimal buyer base-stock levels. The average optimal base-stock levels from numerical simulations for 80%, 85%, 90%, and 100% are 541.06, 513.97, 484.80, 436.63, respectively. Then, as shown in Scenario 1b, we compute the heuristic base-stock levels for the four fill rates using the pooled demand that follows a normal distribution ($D_t \sim N(\mu_D, \sigma_D^2)$; $\mu_D = 400$, $\sigma_D = 40\sqrt{2}$). From Equation (3.7), the pooled base-stock levels are calculated as 518.15, 498.15, 478.15, 438.15, respectively. The results are shown in Table 3.6. Consistent with our results in Scenario 1b, except for the 100% fill rate case, the one sample t-test shows that the values obtained from numerical simulations are significantly different (at $p = 0.05$ level) from the values calculated from the model, once again showing that our heuristic may be underestimating the optimal base stock levels under the normal demand distribution.

Table 3.6: Scenario 2b Simulation Results vs. Heuristic Results

	Simulation Results				Heuristic Results
	Mean	Std. Dev.	Count	Std. Err.	S_B^*
80% Fill Rate	541.06	30.77	100	3.08	518.15
85% Fill Rate	513.97	28.93	100	2.89	498.15
90% Fill Rate	484.80	23.64	100	2.36	478.15
100% Fill Rate	436.63	8.32	100	0.83	438.15

Mathematically, the second scenario is identical to a centralized two-buyers case, where the shared goal of the buyers is to maximize the two buyers' total profit. We next analyze the case of two independent buyers, which corresponds to the decentralized two-buyers case.

3.3 Analysis of the Two-Buyer Case

In this section, we focus on the case of two independent buyers, who do not compete in the end market (i.e., they serve independent demand streams) but optimize their individual profits and are sourced from the same supplier as in Chapter 2. To make the problem tractable, we only analyze the uniform allocation scenario, where the supplier allocates inventory equally between the two buyers if the sum of the orders exceeds available inventory.

While we do not provide analytical results for this case due to analytical complexity, we use numerical simulation to understand the optimal base-stock levels of the buyers to compare against the empirical observations from the lab experiments in the next chapter. The simulation assumes the same target base-stock level for each buyer as an equilibrium solution.[5]

We first conduct simulation for the case where consumer demand for each market follows an independent and identical uniform distribution in each period (Scenario 3a). The average optimal base-stock levels for each buyer obtained through simulations for 80%, 85%, 90%, and 100% fill rate from the supplier are 252.17, 247.32, 243, 233.09, respectively. The results are shown in Table 3.7. These values are higher than the values in the centralized buyers' case above (for a single buyer/market, 241.6, 236.27, 230.64, 219.47, respectively), indicating that centralization helps reduce the inventory levels in the supply chain, as expected.

Table 3.7: Scenario 3a Simulation Results

	Simulation Results			
	Mean	Std. Dev.	Count	Std. Err.
80% Fill Rate	252.17	7.34	100	0.734
85% Fill Rate	247.32	6.74	100	0.674
90% Fill Rate	243.00	6.18	100	0.618
100% Fill Rate	233.09	3.76	100	0.376

Finally, we consider the case where consumer demand for each market follows an independent and identical normal distribution in each period ($\sim N(\mu_D, \sigma_D^2)$; $\mu_D = 200$, $\sigma_D = 40$) (Scenario 3b). From numerical simulations, the average optimal buyer base-stock levels for the four fill rate cases are found as 277.38, 263.99, 249.85, 226.04, respectively. The results are provided in Table 3.8.

Although we cannot claim that a static base stock policy is optimal over a finite horizon under uniform capacity allocation, the base-stock level under 85% fill

[5] We investigated each buyer's best response to a number of different ordering strategies from the other buyer, and the base stock policy proved to give the highest profits for both buyers.

Table 3.8: Scenario 3b Simulation Results

	Simulation Results			
	Mean	Std. Dev.	Count	Std. Err.
80% Fill Rate	277.38	15.07	100	1.51
85% Fill Rate	263.99	12.99	100	1.30
90% Fill Rate	249.85	10.94	100	1.09
100% Fill Rate	226.04	4.11	100	0.41

rate ($263.99 \approx 264$) given in Table 3.8 provides us a benchmark to compare against the empirical observations in the next chapter. We also note that the single buyer heuristic results provide a reasonable approximation for the two independent buyers case. In particular, when we compare the base stock levels obtained from the heuristic under normal distribution (Table 3.4) against the optimal base stock levels from numerical simulation in Table 3.8, we find that the resulting profit loss ranges from 0.02% to 0.23%, given a supplier fill rate of 85%, which is relatively small.[6] Thus, we conclude that our heuristic base stock level is a reasonable approximation to the buyers' equilibrium base stock level, which motivates us to use Equation (3.7) in estimating perceived cost ratios in the next chapter.

3.4 Conclusions

In this chapter, we characterized a buyer's optimal base stock level in a two-stage supply chain, considering a similar framework as in Chapter 2, using analytical and numerical simulation approaches. We first presented a single-buyer base-stock inventory model with a supplier that provides 100% fill rate and then one that provides less than 100% fill rate. Next, we compared our theoretical results to numerical simulations for both uniformly and normally distributed consumer demand. The results showed that our heuristic approximation (Equation (3.7)) estimates the optimal

[6] The comparison between the simulated optimal base stock level and the heuristic base stock level is conducted using the realized demand streams in the experiments across 39 buyer pairs.

base-stock levels well for uniformly distributed demand, but may underestimate for normally distributed demand. We then utilized a numerical simulation approach for the two-buyer case, where the supplier allocates inventory equally between the two buyers if the orders exceed available inventory, for both uniformly and normally distributed consumer demand. In Chapter 4, we use the simulation results from this scenario (Scenario 3b) as a theoretical benchmark against the *actual buyer ordering behavior* observed in our behavioral experiments in Chapter 2.

Chapter 4

Investigating Buyers' Ordering Behavior in a Two-Stage Supply Chain

4.1 Introduction

In many industries with high capacity expansion costs, a supplier who serves multiple buyers may have to allocate limited capacity to each buyer instead of expanding capacity. Inventory rationing has been considered as one of the causes of the bullwhip effect, a phenomenon frequently observed in supply chains where the demand and order variabilities are amplified as one moves up in the supply chain (Lee et al., 1997a). When supply shortage is expected, buyers may also inflate order quantity beyond what they need if they anticipate that they will not be able to receive what they order (Cachon and Lariviere, 1999b). Hewlett-Packard (Lee et al., 1997a), Proctor & Gamble (Lee et al., 1997a), and many firms in the semiconductor manufacturing industry (Terwiesch et al., 2005) have suffered due to the presence of inflated or "phantom" orders that do not quite reflect the "true" demand.

A supplier's capacity allocation mechanism can affect the buyers' order inflation behavior. Suppliers can choose to allocate their scarce capacity equally among their buyers (i.e., uniform allocation policy), or do it in proportion to the actual orders placed by the buyers (i.e., proportional allocation policy) (Cachon and Lariviere, 1999a). Using a single period inventory model, Cachon and Lariviere (1999b) analytically show that under uniform allocation policy from the supplier, buyers do not inflate order quantity even when supply shortage is expected, while under proportional allocation policy buyers inflate order quantity as allocation is proportional to their order quantity. Under these circumstances, one would expect rational buyers to follow these behaviors in practice. However, to the best of our knowledge, the impact of uniform allocation mechanism on reducing the order inflation behavior has not been investigated empirically in the literature. In this study, we investigate in a behavioral context how buyers make their ordering decisions when inventory rationing exists. In particular, since uniform allocation policies have been shown to be "truth-inducing" in analytical models, we investigate the effect of uniform allocation on buyers' ordering behavior. Analytical models typically assume that buyers are fully aware of the supplier's allocation policy. However, in practice, suppliers may not entirely disclose their allocation policies to their buyers (Krishnan et al., 2007), affecting buyers' behavior. Thus, we also investigate the impact of the supplier's communication about his allocation policy.

Most analytical studies based on economic theory and several empirical methodologies such as structural estimation modeling assume rational buyers who make optimal decisions, while behavioral operations management (OM) literature has shown that human decisions often deviate from the optimum. When we compare the benchmark results from the previous chapter with the actual decisions of the buyers in our experiments (from Chapter 2), we find that "human" buyers mark a lower profit performance, where the loss ranges from 0.8% to 14.1%, suggesting that human buyers are not fully rational. Thus, consistent with the findings in the behavioral OM literature, we find that buyers are prone to make suboptimal ordering decisions. From this result, a question arises: What factors affect buyers' ordering decisions? In this chapter, to address this question, we analyze the buyers' ordering behavior using maximum likelihood estimation and structural estimation modeling techniques.

We first investigate whether buyers underweight the supply line, i.e., do not fully consider the on-order quantity from the supplier, using a maximum likelihood estimation approach. We indeed find that regardless of the information disclosure, buyers significantly underweight the supply line. In addition, buyers tend to place a higher weight on the previous period's demand in their ordering decisions when they do not have any information on the allocation policy. This consistently holds in both the initial and later periods of the game.

We next estimate buyers' perceived cost ratios (the ratio between inventory holding cost and backlogging cost) using structural estimation modeling, and investigate the factors that affect these ratios. We find that when buyers do not have information about the allocation policy, they seem to be putting more weight on the inventory holding cost compared to the case with information. Moreover, consistent with the findings for supply line underweighting, our analyses show that when information on the allocation policy is not disclosed, the effect of the state factors on the perceived cost ratios is generally larger than the case with information; however, the differences become negligible over time as the decisions stabilize.

4.2 Literature Review

The bullwhip effect refers to the amplification in order variability as one moves upstream in the supply chain from retail to the source of production. Existing studies attribute the bullwhip effect to both operational and behavioral causes. Operational causes refer to structural elements that cause rational supply chain members to amplify demand variation (Croson et al., 2014). Lee et al. (1997b) identify four operational sources of the bullwhip effect: demand signal processing, inventory rationing and shortage gaming, order batching, and price variations. Theoretically, if only operational causes induce the bullwhip effect, once these operational causes are removed, the bullwhip effect should no longer be observed. However, even when those operational causes are all removed, the bullwhip effect is still observed in lab experiments using the classical four-echelon beer game (Croson and Donohue, 2003, 2006). Croson and Donohue (2006) attribute this phenomenon to "underweighting the supply line," where players may not account for the previous orders that have not yet been received from their supplier ("on-order quantity" in this chapter) when placing orders in the next period (Sterman, 1989). In addition, while demand information sharing between supply chain partners has been widely agreed to mitigate the bullwhip effect (Lee et al., 1997b), the tendency of underweighting the supply line is observed even when the point-of-sales data is shared under common knowledge of uniformly distributed demand (Croson and Donohue, 2003). Moreover, while shorter lead time (i.e., shorter supply line) results in reductions in inventory holding and backorder costs (Steckel et al., 2004), the bullwhip effect and the supply line underweighting are still detected even with zero lead time and without serial demand correlations (Zhao and Zhao, 2015).

Another related research stream is on capacity allocation policies, where a supplier needs to make an allocation decision when the total demand from his buyers exceeds available inventory. In "individually responsive" policies such as proportional, a buyer can receive a larger allocation by placing a larger order, which motivates the buyer to act strategically and inflate her order (Cachon and Lariviere, 1999a,b). On the other hand, with uniform allocation, truth-telling behavior is shown to be a dominant Nash equilibrium (NE) and there is no order inflation. Behavioral studies on capacity allocation focus on proportional allocation mechanisms in one-shot games, and find that NE exaggerates buyers' tendency to strategically order more than they need. Chen et al. (2012) and Chen and Zhao (2015) develop a behavioral model based on the quantal response equilibrium under deterministic and stochastic demand, respectively, while Cui and Zhang (2017) propose a behavioral model based on cognitive hierarchy theory. To the best of our knowledge, uniform allocation mechanism has not been empirically investigated in a behavioral context, which we do in this study. In Chapter 2, we showed that the bullwhip effect is reduced when the allocation policy is communicated. Also, we discussed the results of a fixed-effects regression to demonstrate that buyers underweight the supply line. In this chapter, we investigate this further for uniform allocation using maximum likelihood estimation techniques.

In addition to the over-ordering and supply line underweighting behavior of buyers, the rationality of supply chain players is frequently studied in the behavioral OM literature. Based on studies in the experimental economics and the psychology of individual choices under bounded rationality, Sterman (1989) shows that individual decisions in a beer game systematically deviate from the optimal behavior based on existing analytical inventory models. Consistent to anchoring and insufficient adjustment pattern, one of the human decision making heuristics shown by Tversky and Kahneman (1974), Sterman (1989) finds that the desired stock levels of buyers strongly anchor to their initial choice and that buyers tend to make insufficient adjustments due to the failure of adequately accounting for the supply line. Building on these findings, Schweitzer and Cachon (2000) provide two explanations using anchoring and insufficient adjustment heuristics (i.e., demand-chasing and mean anchoring) about how managers actually make ordering decisions that deviate from the expected profit-maximizing quantity. Gavirneni and Xia (2009) investigate various buyer order-anchoring patterns of newsvendors in a behavioral experiment, and observe that buyers tend to choose an anchor that is close to the optimum. Considering service level contracts, Bolton et al. (2016) examine whether buyers' ordering decisions anchor to the contracted commitment quantity, and do not find a significant anchoring pattern. However, interpreting its directional consistency, they suspect that if there was an anchoring at the beginning of the experimental periods, buyers might have learned over time and appropriately adjusted their decisions. In this chapter, we also show that human buyers are not necessarily fully rational by comparing the profit performances between the simulated buyers with optimized target base-stock policies and the human buyers in the behavioral experiments. In addition, to identify the factors that influence the decisions of buyers, we estimate the (perceived) overage/underage cost ratios of buyers using structural estimation modeling, and investigate how the perceived cost ratio is influenced by various factors.

Over the last decade, the usage of structural estimation modeling framework to estimate behavioral parameters of interest has increased in the area of behavioral OM. The parameters estimated in the behavioral OM literature include (1) overage/underage cost ratios (Olivares et al., 2008; Ho et al., 2010), (2) the level of strategic thinking of buyers (Cui and Zhang, 2017), (3) willingness-to-pay for eliminating the supply and demand mismatch (Kremer and Wassenhove, 2014), (4) distributional and peer-induced fairness (Ho et al., 2014), (5) experience-weighted attraction model parameters (Feng and Zhang, 2017), and (6) reference points in revenue sharing contracts (Becker-Peth and Thonemann, 2016). Using a healthcare application within the newsvendor context, Olivares et al. (2008) find that the hospital of focus in their study tends to perceive the costs of OR idle time (i.e., overage) as approximately 60% higher, on the average, than the cost of schedule overruns and long working times for their staff (i.e., underage). Also in a newsvendor context, Ho et al. (2010) propose a new behavioral model with reference dependence, incorporating the psychological costs of leftover (i.e., overage) and stockouts (i.e., underage), and show that the psychological cost of a leftover is 1.53 times greater than the psychological cost of a stockout. In this chapter, we structurally estimate the overage/underage cost ratios for each individual and each period in a two-stage supply chain, and investigate how the perceived cost ratios of buyers are influenced by various factors such as state variables (e.g., on-order quantity, on-hand inventory, backlog), information on the supplier's capacity allocation policy, and learning over time.

4.3 Research Approach and Results

In the previous chapter, we derived base stock levels for buyers through numerical simulation to use as a benchmark for the ordering behavior observed in our experiments. Although we cannot claim that a static base stock policy is optimal over a finite horizon under uniform capacity allocation, these base-stock levels still provide an "approximately optimal" strategy for a rational buyer. In this chapter, we show how actual ordering behaviors deviate from these benchmark ordering strategies and the resulting deterioration in the achieved profits. In order to investigate why buyers are prone to suboptimal decisions, we also estimate the perceived overage (inventory holding) vs. underage (backlogging) cost ratios for each player (and each period) using structural estimation modeling, and further investigate the factors that affect this ratio using fixed-effect regression analyses.

4.3.1 Model Structure and Key Notation

In our model, consistent with the previous chapters, both the supplier and buyers place orders following a base-stock policy. The supplier's production lead time is assumed to be 4 periods, while delivery time to the buyer is negligible and assumed to be zero. When the supplier receives orders from the buyers, the orders are fulfilled immediately from the supplier's on-hand inventory, while unfulfilled orders are backlogged, referred to as the on-order quantity, to be fulfilled in the next periods. Key notation for this chapter are provided in Table 4.1.

4.3.2 Comparison against theoretical results

At the beginning of each period, each buyer places an order to raise her inventory position back to the target base-stock level, S_B. Since the supplier employs a base-stock policy with a non-zero lead time, the buyer order in each period may not be fulfilled immediately. Consequently, the buyer may not have enough on-hand inven-

Table 4.1: Key Notation

Notation	Definition
S_B	Buyer's base-stock level
p	Unit revenue (selling price)
c	Unit procurement cost
h	Unit inventory holding cost
b	Unit backlogging cost
β	Supplier's target fill-rate to the buyer ($0 < \beta \leq 1$)
D_t	Consumer demand realized by the buyer in period t
O_t	Order quantity placed by the buyer at the beginning of period t
R_t	Received shipment by the buyer at the beginning of period t
$\mathcal{N}_t$	On-order quantity the supplier owes the buyer at the end of period t
IL_t:	Inventory level of the buyer at the beginning of period t
IP_t:	Inventory position of the buyer before placing an order in period t
I_t:	On-hand inventory of buyer i at the end of period t
B_t:	Backlog of buyer i at the end of period t
π_t	Buyer's profit for period t

tory to fulfill consumer demand. The buyer backlogs any unmet consumer demand incurring a unit backlogging cost, b, to fulfill in the next periods. In case there is leftover inventory after serving demand at the end of each period, the inventory is carried over to the next period with unit inventory holding cost, h.

In Chapter 3, using normally distributed consumer demand ($\sim N(\mu_D, \sigma_D^2)$; $\mu_D = 200$, $\sigma_D = 40$), unit selling price of $p = \$2$, unit procurement cost of $c = \$1$, unit inventory-holding cost of $h = \$0.15$, and unit backlogging cost of $b = \$0.45$, and supplier's fill rate of $\beta = 85\%$, we obtained the optimal (static) target base-stock level as 264 through numerical simulation. To compare the profit performances of this benchmark base-stock policy and the actual buyer behavior in our experiments, we first calculate the total profit for each pair of buyers in the experiments. Then, using the same demand streams that the buyers faced during the experiments, we calculate the profit performances of the base-stock ordering policy (with the static target base-stock level of 264) for each pair of buyers from the simulation. For profit comparisons, we look into **NI/UNI** and **I/UNI** treatments, introduced in Chapter 2. Recall that **NI/UNI** is the uniform allocation treatment without information about the allocation policy, while **I/UNI** is that with information. For the **NI/UNI** treatment, using a two-tailed paired t-test, we find that the profit difference between experiments and the simulation is statistically significant ($p < 0.0001$). In particular, the lowest total profit obtained in the simulation across all demand scenarios is 18,926.5, while the highest total profit that any buyer pair achieved in the experiments was 18,827.6. We further look into each individual player's profit performance, and find that only one buyer out of the 38 buyers[1] could achieve slightly higher profits than the simulation results (0.4%).[2] For the **I/UNI** treatment, using a two-tailed paired t-test, we find that the profit difference between experiments and the simulation is also statistically significant ($p < 0.0001$). The lowest total profit obtained in the simulation across all demand scenarios is 18,893.8, while the highest total profit that any buyer pair achieved in the experiments was 18,814.5. We also look into each individual player's profit performance, and find that only three buyers out of the 40 buyers could achieve slightly higher profits than the simulation results (0.2%, 0.3%, 0.7%, respectively). Summary statistics for buyers' profit performances in the simulations vs. experiments under both treatments are provided in Table 4.2.[3]

In summary, we find that the human buyers in the experiments had lower profits than the simulated buyers in the range of 0.8% to 14.1%.[4] We next investigate the drivers of the buyers' ordering behavior.

[1]Note that we include one additional pair in this chapter which was removed in Chapter 2 due to significantly inflated forecasts. Since the ordering decisions did not show any anomalies, we chose to include them in the ordering behavior analysis.

[2]Note that each buyer's decisions are affected by the other buyer's decisions in the experiment, given the supplier's allocation policy, while the simulation is based on an "equilibrium" assumption.

[3]As discussed in Chapter 2, the difference in profit performances of the buyers in our experiments under **NI/UNI** and **I/UNI** treatments is not statistically significant ($p = 0.2725$) using a two-tailed heteroskedastic t-test due to the unequal variances.

[4]Specifically, 0.8% to 12.7% for **NI/UNI** treatment, and 1.1% to 14.1% for **I/UNI** treatment.

Table 4.2: Summary Statistics for Total Buyer Profits in Experiments vs. Simulations

	NI/UNI (19 buyer pairs)				
	Max	Min	Median	Mean	Std. Dev.
Simulation	19,043.1	18,926.5	18,980.6	18,986.3	24.63
Experiments	18,827.6	16,561.1	18,345.3	18,154.8	570.4
	I/UNI (20 buyer pairs)				
	Max	Min	Median	Mean	Std. Dev.
Simulation	19,040.9	18,893.8	18,993.4	18,993.5	36.4
Experiments	18,814.5	16,228.8	18,503.4	18,357.7	566.7

4.3.3 Supply Line Underweighting

We first investigate whether subjects underweight the supply line using the experiments from Chapter 2 with uniform allocation. A base stock policy could have been optimal for the buyers in the absence of inventory rationing (a buyer's order is not guaranteed to be fully met under a capacity allocation policy). Let S_B denote the base stock level for the buyers. Note that buyers need to make a decision before consumer demand is realized. After placing an order equal to the base stock level (S_B^*) in period 1, buyer i would order enough to raise his inventory position (IP_{it}^b) back to the target base stock level in each period, given by the demand of the previous period ($D_{i,t-1}$):

$$O_{it} = S_B^* - IP_{i,t-1}^b + D_{i,t-1} \qquad \text{for } i = 1, 2;\ t = 2, ..., T \tag{4.1}$$

We can rewrite (4.1) as:

$$O_{it} = S_B^* - IL_{i,t-1}^b + D_{i,t-1} - R_{i,t-1} - \mathcal{N}_{i,t-1} \qquad \text{for } i = 1, 2;\ t = 2, ..., T \tag{4.2}$$

where $IL_{it}^b = I_{i,t-1} - B_{i,t-1}$ denotes buyer i's inventory level at the beginning of period t. Since we do not know the base stock level chosen by a buyer, we can write the estimation problem for (4.2), utilizing the notation in Croson and Donohue (2006) and Niranjan et al. (2011), as follows:

$$O_{it} = \alpha_0 + \alpha_I IL_{i,t-1}^b + \alpha_D D_{i,t-1} + \alpha_R R_{i,t-1} + \alpha_N \mathcal{N}_{i,t-1} + \varepsilon \tag{4.3}$$

for $i = 1, 2;\ t = 2, ..., T$. We can also write a modified version of this equation replacing $(\alpha_I IL^b_{t-1})$ with $(\alpha^+_I I_{t-2} + \alpha^-_I B_{t-2})$ to estimate the effects of on-hand inventory and backlog separately:

$$O_{it} = \alpha_0 + \alpha^+_I I_{t-2} + \alpha^-_I B_{t-2} + \alpha_D D_{i,t-1} + \alpha_R R_{i,t-1} + \alpha_N \mathcal{N}_{i,t-1} + \varepsilon \tag{4.4}$$

for $i = 1, 2;\ t = 2, ..., T$. In theory, it should hold that $\alpha_I = \alpha_R = \alpha_N = -1$ and $\alpha_D = 1$, while if *underweighting the supply line* exists, we should find $\alpha_N > \alpha_I$ and $-1 < \alpha_N < 0$.

Supply Line Underweighting - All Periods of the Game

We estimate Equations (4.3) and (4.4) using maximum likelihood estimation. We use clustered standard errors at the buyer-pair level to control for the pair-level effects, in addition to controlling for individual-level and period-level fixed effects. The results are given in Table 4.3.

We observe that all coefficients have signs consistent with the formulation. We first investigate the coefficient of on-order quantity, α_N, to see the extent of the supply line underweighting. While the magnitude of the coefficient is similar between **NI/UNI** and **I/UNI** treatments, it is statistically significant for the latter but not for the former.[5] Overall, the coefficient is closer to 0 than -1; i.e., significantly smaller than the theorized effect. We test whether the α_N estimate is significantly different from -1 using a two-tailed t-test, which strongly rejects the null hypothesis under both treatments.[6] We next test whether α_N is significantly greater than α_I,

[5]For the α_N estimate under **I/UNI** treatment, $p = 0.046$ for Eqn. (4.3) and $p = 0.063$ for Eqn. (4.4), while under **NI/UNI** treatment, $p = 0.761$ for Eqn. (4.3) and $p = 0.776$ for Eqn. (4.4). Moreover, the difference in the coefficients between the two treatments is not statistically significant. The z-statistic is 0.038 for Eqn. (4.3) and 0.001 for Eqn. (4.4). Both z-statistics are smaller than the z-critical value, 1.645, at $\alpha = 0.1$ level.

[6]Under **I/UNI** treatment, t-statistic is 149.65 for Eqn. (4.3) and 164.26 for Eqn. (4.4), while under **NI/UNI** treatment, 24.35 for Eqn. (4.3) and 23.95 for Eqn. (4.4). All four t-statistics are greater than the t-critical value, 2.58, at $\alpha = 0.01$ level.

Table 4.3: Maximum Likelihood Estimation of Equations (4.3)-(4.4) for All Periods

	(4.3)		(4.4)	
	NI/UNI	**I/UNI**	**NI/UNI**	**I/UNI**
$D_{i,t-1}$	0.871***	0.640***	0.868***	0.681***
	(0.0794)	(0.0762)	(0.0811)	(0.0752)
$R_{i,t-1}$	-0.306***	-0.0995	-0.307***	-0.115*
	(0.0499)	(0.0657)	(0.0498)	(0.0604)
$\mathcal{N}_{i,t-1}$	-0.0125	-0.0141**	-0.0119	-0.0119*
	(0.0406)	(0.00659)	(0.0413)	(0.00602)
$IL_{i,t-1}$	-0.383***	-0.178***	-	-
	(0.0353)	(0.0330)		
$I_{i,t-2}$	-	-	-0.394***	-0.164***
			(0.0392)	(0.0302)
$B_{i,t-2}$	-	-	0.362***	0.370***
			(0.0981)	(0.0659)
Intercept	74.51***	138.59***	75.96***	125.02***
	(18.10)	(22.61)	(19.91)	(25.13)
N	1824	1920	1824	1920
$Adj.R^2$	0.452	0.211	0.452	0.215

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors (pair-level) are in parentheses.

and the difference is statistically significant.[7] Thus, *buyers underweight the supply line even when uniform allocation policy is implemented with communication.*

We next observe that the coefficient of the inventory level, α_I, is significantly different between the two treatments.[8] A closer look into Equation (4.4) reveals that the difference is primarily from the effect of on-hand inventory while the effect of backlog seems similar. In particular, *buyers seem to put a higher weight on on-hand inventory levels when they do not have information about the allocation policy.* We also observe

[7]Consistent with the literature, Eqn. (4.3) is used for comparison: z-statistics under **I/UNI** treatment is 4.88, while under **NI/UNI** treatment 6.88. Both z-statistics are greater than z-critical value, 2.58, at $\alpha = 0.01$ level.

[8]The z-statistic for α_I is 4.23, greater than the z-critical value, 2.58, at $\alpha = 0.01$ level. The z-statistic is 4.64 for α_I^+, and 0.068 for α_I^-.

differences in the coefficients of previous demand[9] and received shipment[10] in both equations. Under a base-stock policy with a fully reliable supplier, once the target base-stock level is reached, the ordering decision in each period is to place an order that equals the previous period's demand, which is not necessarily the case under a supplier with less than 100% fill rate. Our results from a two-tailed t-test show that under **I/UNI** treatment, the coefficient of demand (α_D) is significantly different from 1 (t-statistic: 4.72 $>$ t-critical: 2.58 at $p = 0.01$ level), while under **NI/UNI** treatment, the coefficient of demand is not significantly different from 1 (t-statistic: 1.62 $<$ t-critical: 2.58). Thus, *buyers seem to rely more on the previous period's demand when they do not have any information on the allocation policy.*[11]

As a robustness check, we also compare the coefficients between the two treatments using regression models involving full interaction terms between the communication dummy variable and the independent variables in Equations (4.3) and (4.4), and obtain results consistent with z-tests.[12]

[9]The difference in the coefficients under **NI/UNI** treatment and **I/UNI** treatment is statistically significant for Eqn. (4.3) and marginally significant for Eqn. (4.4). For Eqn. (4.3), the z-statistic is 2.09, which is greater than the z-critical value, 1.96, at $\alpha = 0.05$ level. For Eqn. (4.4), the z-statistic is 1.70, greater than the z-critical value, 1.65, at $\alpha = 0.1$ level.

[10]The z-statistic is 2.50 for Eqn. (4.3), and 2.44 for Eqn. (4.4). Both z-statistics are greater than the z-critical value, 1.96, at $\alpha = 0.05$ level.

[11]We test for multi-collinearity by checking variance inflation factors (VIFs) for the independent variables in both equations. The maximum VIFs in both equations do not exceed 3, considerably less than the rule of thumb of 10 (Kutner et al., 2004). The mean VIFs in Equations (4.3) and (4.4) under **NI/UNI** are 2.03 and 2.02, and under **I/UNI** treatment are 2.00 and 2.02. These results indicate that multi-collinearity does not constitute a serious issue in either model.

[12]In Eqn. (4.3), the coefficients of inventory level, demand, and received shipment are significantly or marginally significantly different (with p-values of 0.022, 0.067, 0.059, respectively), while the coefficients of on-order quantity do not differ significantly (with a p-value of 0.306). In Eqn. (4.4), the differences in the coefficients of on-hand inventory, demand, and received shipment are significant or marginally significant (with p-values of 0.016, 0.072, 0.085, respectively), while the differences in the coefficients of backlog and on-order are not significant (with p-values of 0.380 and 0.215).

Supply Line Underweighting - Second Half of the Game

As shown in Chapter 2, since the second half of the game (i.e., periods 26-50) provides more stable results, we next concentrate our analysis on the second half of the game only. The maximum likelihood estimation results using Equations (4.3)-(4.4) are provided in Table 4.4. Consistent with the all-periods analysis, we use clustered standard errors at the buyer-pair level to control for the pair-level effects, and control for the period-level and individual-level fixed effects.

Table 4.4: Maximum Likelihood Estimation of Equations (4.3)-(4.4) for 2^{nd} Half

	(4.3)		(4.4)	
	NI/UNI	**I/UNI**	**NI/UNI**	**I/UNI**
$D_{i,t-1}$	0.857***	0.726***	0.854***	0.725***
	(0.0995)	(0.101)	(0.0994)	(0.102)
$R_{i,t-1}$	-0.410***	-0.383***	-0.410***	-0.383***
	(0.0599)	(0.0570)	(0.0603)	(0.0560)
$\mathcal{N}_{i,t-1}$	-0.117**	-0.0788	-0.104**	-0.0775
	(0.0471)	(0.0889)	(0.0469)	(0.0917)
$IL_{i,t-1}$	-0.435***	-0.424***	-	-
	(0.0507)	(0.0716)		
$I_{i,t-2}$	-	-	-0.475***	-0.428***
			(0.0699)	(0.0802)
$B_{i,t-2}$	-	-	0.332***	0.409***
			(0.0930)	(0.0623)
Intercept	118.04***	177.25***	123.04***	177.68***
	(19.02)	(20.95)	(17.67)	(21.76)
N	950	1000	950	1000
$Adj.R^2$	0.507	0.452	0.511	0.452

*** p<0.01, ** p<0.05, * p<0.1
Clustered robust standard errors (pair-level) are in parentheses.

We again find that all coefficients have signs consistent with the formulation. Moreover, the differences in the coefficients between the two treatments become insignificant in "steady state."[13] This indicates that *providing information on the al-*

[13]In Eqn. (4.3), the z-statistics for $D_{i,t-1}$, $R_{i,t-1}$, $N_{i,t-1}$, and $IL_{i,t-1}$ are 0.920, 0.323, 0.377, 0.115, respectively. In Eqn. (4.4), the z-statistics for $D_{i,t-1}$, $R_{i,t-1}$, $N_{i,t-1}$, $I_{i,t-1}$, and $B_{i,t-1}$ are 0.902, 0.319, 0.260, 0.447, 0.688, respectively. All nine z-statistics are smaller than the z-critical value, 1.65, at $\alpha = 0.1$ level, indicating that the differences are no longer significant in the 2^{nd} half.

location policy affects buyers' ordering behavior more prominently in the early stages of the game, where buyers are still learning, while the differences become smaller over time as the target base-stock levels gradually stabilize. We provide graphs of the buyers' average inventory positions under **NI/UNI** and **I/UNI** treatments over 50 periods in Figure 4.1. We observe that the inventory positions for both treatments fluctuate around the simulated optimum, i.e., 264, in the second half of the game.

As a robustness check, we also test the differences in the coefficients between the two treatments using regression models extended from Equations (4.3) and (4.4) with full interaction terms, and obtain the same results.[14]

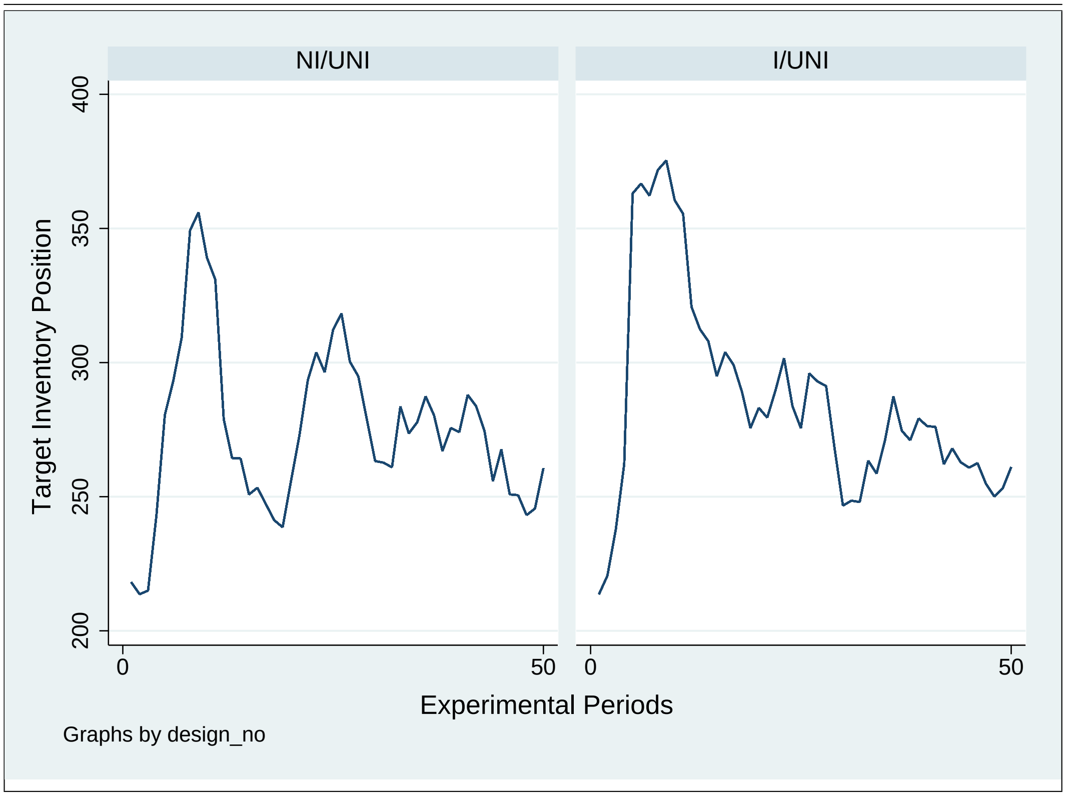


Figure 4.1: Buyers' Average Inventory Positions under **NI/UNI** and **I/UNI** Treatments

[14]In Eqn. (4.3), the coefficients of inventory level, demand, received shipment, and on-order quantity are not significantly different between the two treatments (with p-values of 0.829, 0.420, 0.429, 0.614, respectively). In Eqn. (4.4), the differences in the coefficients of on-hand inventory, backlog, demand, received shipment, and on-order quantity are not significant (with p-values of 0.716, 0.702, 0.421, 0.459, 0.735, respectively).

We also test whether α_N estimate is significantly different from -1 using a two-tailed t-test, and find that the null hypothesis is rejected under both treatments.[15] We then test whether α_N is significantly greater than α_I, and find that the difference is statistically significant.[16] Thus, even in the second half of the game with more stable inventory positions, buyers continue to underweight the supply line.

We also observe that the coefficient of demand (α_D) under **I/UNI** treatment is higher in the second half, while a two-tailed t-test still shows that the coefficient is statistically significantly different from 1 (t-statistic: 2.71 > t-critical: 2.58 at $p = 0.01$ level), which is not the case under **NI/UNI** treatment (t-statistic: 1.44 < t-critical: 2.58 at $p = 0.01$ level), consistent with the all-periods analysis. Although the difference in the coefficients between the two treatments is not statistically significant, these results suggest that buyers may continue to rely on the previous period's demand slightly more when they do not have any information on the allocation policy.[17]

4.3.4 Buyers' Perceived Cost Ratios

In Chapter 3, we showed that a single buyer's heuristic base-stock level over an infinite horizon satisfies:

$$F\left(S_B^* - E\left[\mathcal{N}\right]\right) = \frac{b}{h+b} = \frac{1}{\frac{h}{b}+1}. \tag{4.5}$$

In addition, from Tables 3.4 and 3.8, we observe that the optimal base-stock levels based on numerical simulations in the single-buyer (1b) and the two-buyer (3b) sce-

[15] Under **I/UNI** treatment, t-statistics are 10.37 for Eqn. (4.3) and 10.05 for Eqn. (4.4), while under **NI/UNI** treatment, 18.77 for Eqn. (4.3) and 19.10 for Eqn. (4.4). These four t-statistics are all greater than the t-critical value, 2.58, at $\alpha = 0.01$ level.

[16] As in the all-periods analysis, consistent with literature, Eqn. (4.3) is used for the comparison: z-statistic under **I/UNI** treatment is 3.03, while under **NI/UNI** treatment 4.59. Both z-statistics are greater than the z-critical value, 2.58, at $\alpha = 0.01$ level.

[17] We also check VIFs for the independent variables in both equations to test multi-collinearity. The maximum VIFs in both equations is 3.36, considerably less than the rule of thumb 10 (Kutner et al., 2004). In addition, the mean VIFs in Equations (4.3) and (4.4) under **NI/UNI** are 2.06 and 2.06, and under **I/UNI** treatment 2.05 and 2.05. Thus, these results indicate that multi-collinearity does not constitute a serious issue in either model.

narios are similar. Moreover, when we compare the base stock levels obtained from the heuristic in Table 3.4 against the optimal base stock levels from numerical simulation in Table 3.8, we find that the resulting profit loss ranges from 0.02% to 0.23%, given a supplier fill rate of 85%, which is relatively small. Thus, we conclude that our heuristic base stock level is a reasonable approximation to the buyers' equilibrium base stock level, which motivates us to use Equation (3.7) in estimating buyers' perceived cost ratios in this chapter.

Using data from our behavioral experiments, we estimate the buyers' perceived overage/underage cost ratio, $\frac{h}{b}$, through structural estimation modeling. We refer to this cost ratio as γ. Note that the true value of γ in the experiments is $\frac{1}{3}$ since $h = \$0.15$ and $b = \$0.45$. As observed in Equation (4.5) above, we expect the target base-stock level decisions of buyers to be closely tied to γ. In particular, if a buyer's γ value is high (low), the buyer would tend to weight the inventory holding cost more (less) than the backlogging cost, and be more likely to keep a lower (higher) on-hand inventory level than she should. With a target inventory position of S_B and an on-order quantity of $\mathcal{N}_t$, a buyer's available-to-serve inventory level in period t is $S_B - \mathcal{N}_t$. Over the course of the game, it is possible that players update their target base stock levels. Thus, as we fit the inventory model to the experimental data, instead of using the same static target base stock level for each buyer, we rewrite the heuristic base stock equation for buyer i in period t as $F\left(S_{it} - \mathcal{N}_{it}\right) = \frac{1}{\gamma_{it}+1}$.

After transforming the distribution function to a standard normal distribution (Φ) as:

$$F\left(S_{it} - \mathcal{N}_{it}\right) = Pr\left(D \leq S_{it} - \mathcal{N}_{it}\right) = \Phi\left(\frac{S_{it} - \mathcal{N}_{it} - \widehat{X_i \beta}}{\widehat{\sigma_i}}\right) = \frac{1}{\gamma_{it} + 1}$$

we obtain $\gamma_{it} = \frac{1}{\Phi\left(\frac{S_{it} - \mathcal{N}_{it} - \widehat{X_i \beta}}{\widehat{\sigma_i}}\right)} - 1$. In this expression, we need empirical estimates of demand for buyer i, i.e., $\widehat{X_i \beta}$, and thus, we use the coefficients vector for β that is obtained from a rearranged version of Equation (4.4):

$$D_{i,t-1} = \beta_0 + \beta_I^+ I_{i,t-2} + \beta_I^- B_{i,t-2} + \beta_R R_{i,t-1} + \beta_N \mathcal{N}_{i,t-1} + \beta_O O_{it} + \varepsilon \tag{4.6}$$

Using this rearranged equation, we run random-effect and fixed-effect regressions with/without controlling for period-level (time) fixed effects (four regression models).[18] Note that the base-stock level is captured by the intercept and error term in this equation. Additionally, we use the statistics of each individual for X_i. For $\widehat{\sigma_i}$, we use $\sqrt{MSE}$ obtained from each of the four regression models, where MSE denotes mean squared error. For the target base-stock level, S_{it}, we use the observed inventory position, and for the on-order quantity, $\mathcal{N}_{it}$, we use the observed on-order quantity for buyer i in period t. Thus, using experimental data and standardized statistics, we obtain γ_{it} for buyer i in period t calculating $\frac{1}{\Phi\left(\frac{S_{it}-\mathcal{N}_{it}-\widehat{X_i\beta}}{\widehat{\sigma_i}}\right)} - 1$.

Buyers' Perceived Cost Ratios - All Periods

For estimating the buyers' perceived cost ratio, γ_{it}, we first validate, using standard and robust Hausman tests, that the fixed-effects model is more appropriate than the random-effects model. Thus, we focus on the results from the fixed-effects models. Moreover, the R^2 value significantly improves when the time fixed effects are controlled for, which holds for both **I/UNI** and **NI/UNI** treatments. Thus, we mainly refer to the γ_{it} values obtained through fixed-effects regressions with time fixed effects. Summary statistics for γ_{it} are provided in Table 4.5.

We observe that the mean and standard deviation of γ_{it} are very large due to extreme values. Therefore, we look into median values for our analysis. Under **I/UNI** treatment, the median γ_{it} value does not significantly differ between with vs. without time fixed effects, and is fairly close to but slightly smaller than the true value, $\frac{1}{3}$.

[18]This step provides the statistics for demand standardization. Since the coefficients of these regressions at this stage do not have any meaning (other than the usage for standardization), we do not include the regression results in this chapter. However, all results are available upon request.

Table 4.5: Summary Statistics of γ_{it} - All Periods

	NI/UNI	
	Without Time Fixed Effects	With Time Fixed Effects
	(1)	(2)
Median	0.1377	0.3496
Mean	3.26e+31	4.79e+75
Standard Deviation	1.39e+33	2.05e+77
Min	0	0
Max	5.95e+34	8.74e+78
	I/UNI	
	Without Time Fixed Effects	With Time Fixed Effects
	(1)	(2)
Median	0.2831	0.2836
Mean	3.97e+41	1.66e+19
Standard Deviation	1.74e+43	7.29e+20
Min	0	0
Max	7.62e+44	3.19e+22

Thus, as expected, buyers seem to weight the backlogging cost (about 3.5 times) more than the inventory holding cost under this treatment. On the other hand, the estimated γ_{it} value under the **NI/UNI** treatment relies heavily on whether the time fixed effects are controlled for, which alludes to the significance of the learning effect over time for the case without information, as discussed before. In particular, the γ_{it} value gets very close to the true value with the time fixed effects. Overall, *when the buyers do not have information about the allocation policy, they seem to be putting more weight on the inventory holding cost compared to the case with information*, which is in line with our observations from Table 4.3, where the coefficient for on-hand inventory under **NI/UNI** is relatively higher than that under **I/UNI**.

We next present histograms of γ_{it} for both treatments in Figure 4.2. These histograms show similar patterns as in the structural estimation modeling literature (Olivares et al., 2008), and a substantial heterogeneity in the estimated cost ratios. We also provide the histograms of log-transformed γ_{it}, i.e., ln (γ_{it}), in Figure 4.3.[19]

[19] Note that the numbers of observations are different under the two treatments (1,824 under **NI/UNI** and 1,920 under **I/UNI**). We also exclude the extreme γ_{it} values for better visibility.

Since γ_{it} values seem to follow a log-normal distribution, we use ln (γ_{it}) for further analysis. In addition, as the estimated cost ratios contain extreme values (i.e., $\gamma_{it} \geq$10,000), particularly under **NI/UNI** treatment, we provide subsequent results for both models with and without extreme values.

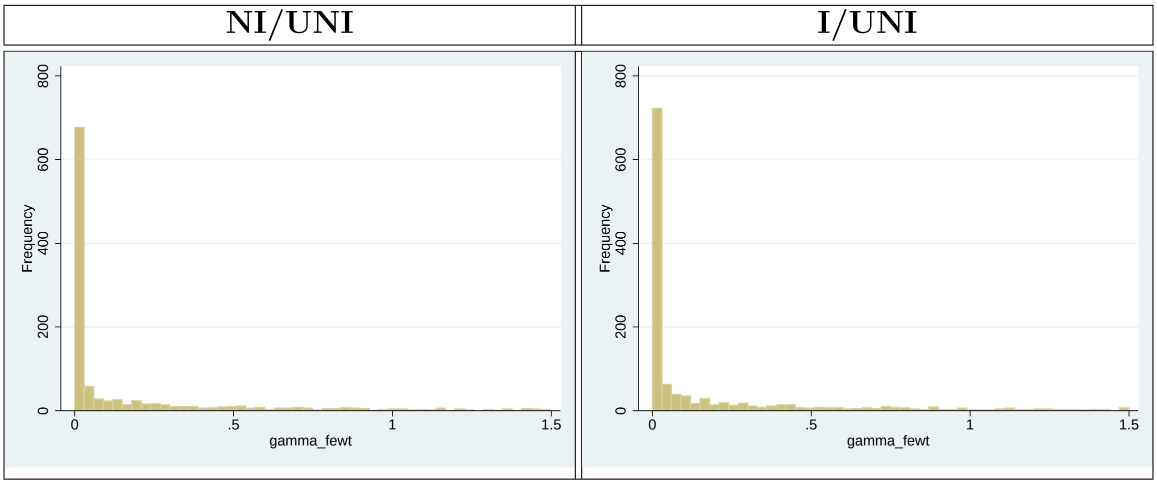


Figure 4.2: Histogram of γ_{it} - All Periods

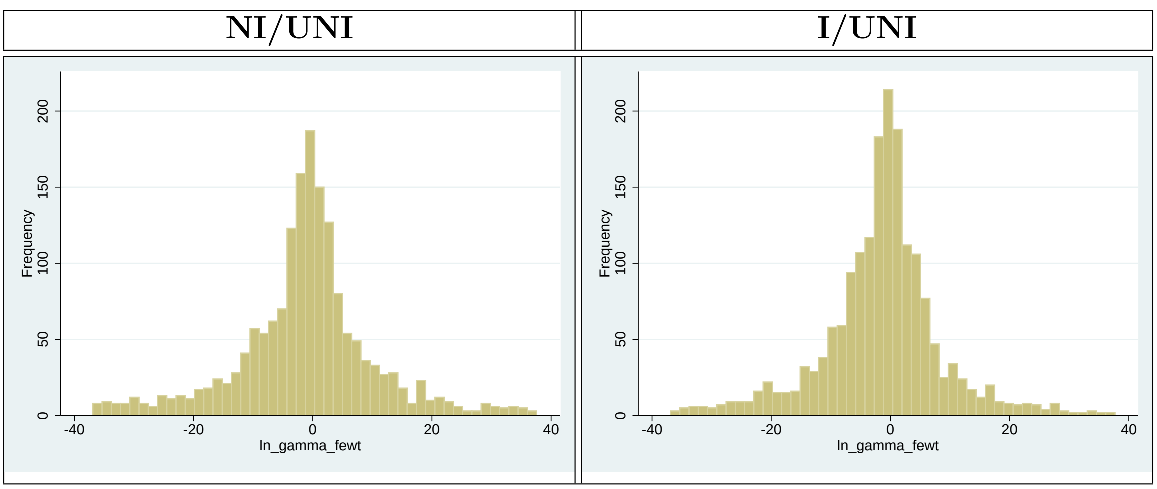


Figure 4.3: Histogram of ln (γ_{it}) - All Periods

To understand the source of the heterogeneity in the γ_{it} values, we examine how a buyer's cost ratio, ln(γ_{it}), is affected by factors such as her on-hand inventory, backlog level, on-order quantity, received shipment, and realized demand. To control for pair-level fixed effects, we conduct clustered fixed-effect regressions at the buyer-pair level. For all models, Hausman tests strongly reject the null hypothesis, indicating that fixed-effects models are more appropriate than random-effects models, and thus, for both treatments, the results from fixed-effects models are shown in Table 4.6.[20]

Table 4.6: Clustered Regressions of ln (γ_{it}) - All Periods with Time Fixed Effects

	ln (γ_{it})			
	NI/UNI		**I/UNI**	
	All Observations	Without Extremes	All Observations	Without Extremes
$I_{i,t-2}$	-0.114***	-0.0842***	-0.0838***	-0.0747***
	(0.01)	(0.01)	(0.01)	(0.01)
$B_{i,t-2}$	0.131***	0.0649***	0.0597***	0.0490***
	(0.02)	(0.01)	(0.01)	(0.01)
$\mathcal{N}_{i,t-1}$	-0.0640***	-0.0424***	-0.0176*	-0.0122
	(0.01)	(0.00)	(0.01)	(0.01)
$R_{i,t-1}$	-0.140***	-0.0855***	-0.0999***	-0.0836***
	(0.01)	(0.01)	(0.01)	(0.01)
$D_{i,t-1}$	0.123***	0.0720***	0.104***	0.0755***
	(0.01)	(0.01)	(0.01)	(0.01)
N	1,708	1,454	1,805	1,621
R^2	0.639	0.669	0.700	0.658
# buyers	38	38	40	40

*** p<0.01, ** p<0.05, * p<0.1
Clustered standard errors are in parentheses.

The coefficients of the independent variables show consistent signs across all regressions. The coefficient of on-hand inventory, $I_{i,t-2}$, is significantly negative under both **NI/UNI** and **I/UNI** treatments, indicating that the buyers with lower on-hand inventory levels tend to have higher γ_{it} values (i.e., put more weight on inventory holding cost in comparison to backlogging cost).[21] Moreover, *when information on allocation policy is not communicated to the buyers, they tend to place a higher weight on the inventory holding cost, as compared to the case with information, particularly*

[20]Note that Table 4.6 provides the results from regression models with time fixed effects controlled. We also provide the results without time fixed effects in Table B.1 in Chapter 4 Appendices.

[21]Including all observations, the coefficient of on-hand inventory under **NI/UNI** treatment is statistically significantly greater than that under **I/UNI** treatment (z-statistic 2.69 $>$ z-critical 2.58, at $\alpha = 0.01$ level), while excluding extreme values, the difference is not statistically significant (z-statistic 0.883 $<$ z-critical 1.65, at $\alpha = 0.1$ level).

when the extreme values are included (which primarily occur in the first half of the game, as will be explained below). On the contrary, the coefficient of backlog, $B_{i,t-2}$, shows a significantly positive relationship under both treatments, indicating that the buyers with lower backlog levels tend to have lower γ_{it} values (i.e, put more weight on backlogging cost relative to inventory holding cost).[22] Moreover, *when information on the supplier's allocation policy is not communicated, the buyers are more sensitive to their backlog levels, particularly under extreme values.*

We also observe that the coefficient for on-order quantity, $\mathcal{N}_{i,t-1}$, is negatively significant under **NI/UNI** treatment, while insignificant (or marginally significant[23] with a very small coefficient) under **I/UNI** treatment. Moreover, the difference between the two treatments is statistically significant, where on-order quantity influences buyers' perceived cost ratios more when information on the allocation policy is not communicated.[24] Thus, *a higher on-order quantity tends to influence the buyers' perceived cost ratios more, emphasizing the backlogging cost, when buyers do not have any information on the allocation policy.*

Overall, the magnitudes of the coefficients under **NI/UNI** seem to be larger than those under **I/UNI**, which indicates that *when buyers do not have information on the supplier's allocation policy, they may act in a more reactive fashion, since their perceived cost ratios are more influenced by their current state, such as on-hand inventory, backlog, and on-order quantity levels.*

As our results tend to change based on the inclusion/exclusion of *extreme values*, we further examine the variability of γ_{it} values. To understand where the extreme

[22]With all observations, the coefficient of backlog under **NI/UNI** treatment is statistically significantly greater than that under **I/UNI** treatment (z-statistic 4.17 $>$ z-critical 2.58, at $\alpha = 0.01$ level), while excluding extreme values, the difference is not statistically significant (z-statistic 1.43 $<$ z-critical 1.65, at $\alpha = 0.1$ level).

[23]Significant at $\alpha = 0.1$ level.

[24]With all observations, z-statistic is 3.85, and excluding extreme values, 3.42. Both are greater than z-critical, 2.58, at $\alpha = 0.01$ level.

values are mostly observed, we first calculate the mean γ_{it} for each individual. Under **NI/UNI**, the extreme values (around 99% percentile) are observed in five subjects[25] out of 38, while under **I/UNI**, an extreme value is observed in only one subject [26] out of 40. We next calculate the mean γ_{it} for each period. Under **NI/UNI**, the extreme values are observed in periods 1, 2, 3, 23, 24, 25, while under **I/UNI**, extreme values are observed in periods 1, 2, 7. As extreme values appear in the first half of the game, it seems that the second half of the game represents more stable decisions as discussed before. Therefore, in the following section, we conduct the structural estimation analysis concentrating on the second half of the game.[27]

Buyers' Perceived Cost Ratios - Second Half of the Game

In this section, we concentrate on the second half of the game (i.e., periods 26-50). Consistent with the all-periods analysis, through standard and robust Hausman tests, we validate that the fixed-effects model is more appropriate than the random-effects model for estimating the buyers' perceived cost ratio, γ_{it}. In addition, the R^2 value significantly improves when the time fixed effects are controlled for, which holds for both **I/UNI** and **NI/UNI** treatments. Therefore, we again refer to the γ_{it} values obtained through fixed-effects regressions with time fixed effects. Summary statistics of γ_{it} are provided in Table 4.7.

Although the magnitudes of the coefficients are reduced in comparison with those in the all-periods analysis, we observe in Table 4.7 that the mean and standard deviation of γ_{it} are again large due to extreme values. Thus, we refer to the median values for our analysis.

[25]Subject are A3B1, A5B2, A7B1, A50B1, A50B2.

[26]Subject is E11B2.

[27]We also test for multicollinearity for all four models under both treatments. We find that the maximum VIF across all four models is 2.76, which does not exceed the rule of thumb 10 (Kutner et al., 2004), while the four mean VIF values range from 1.98 to 2.40, which indicate that multicollinearity is not a serious problem in these models.

Table 4.7: Summary Statistics of γ_{it} - 2^{nd} Half

	NI/UNI	
	Without Time Fixed Effects (1)	With Time Fixed Effects (2)
Median	0.1654	0.1248
Mean	1.92e+10	2.10e+19
Standard Deviation	4.78e+11	6.46e+20
Min	0	0
Max	1.42e+13	1.99e+22
	I/UNI	
	Without Time Fixed Effects (1)	With Time Fixed Effects (2)
Median	0.1491	0.0914
Mean	30403.82	1.26e+08
Standard Deviation	846475	2.85e+09
Min	0	0
Max	2.65e+07	8.05e+10

Under both **NI/UNI** and **I/UNI**, we observe that the median γ_{it} in the second-half of the game significantly decreases in comparison to the all-periods case, while the gap between the two treatments decrease in the second half of the game as decisions stabilize. In particular, the median value decreases from 0.2836 to 0.0914 under **I/UNI**, and from 0.3496 to 0.1248 under **NI/UNI**, which are both considerably smaller than the true value, $\frac{1}{3}$. Thus, *buyers seem to emphasize the backlogging cost significantly more in the second-half of the game.*

We next present histograms of γ_{it} for both treatments in Figure 4.4, which show similar patterns as in the all-periods case, as well as a substantial heterogeneity in the estimated cost ratios. We also provide histograms of the log-transformed γ_{it}, i.e., $\ln(\gamma_{it})$, in Figure 4.5.[28] Although each log-transformed graph shows a slight left shift in comparison to the graphs in the all-periods analysis, the γ_{it} values still seem to follow an approximately log-normal distribution. Therefore, we use $\ln(\gamma_{it})$ for further analysis, to maintain consistency with the all-periods analysis.

[28]Note that the number of observations is different under the two treatments (950 under **NI/UNI** and 1,000 under **I/UNI**). We exclude the extreme γ_{it} values for better visibility.

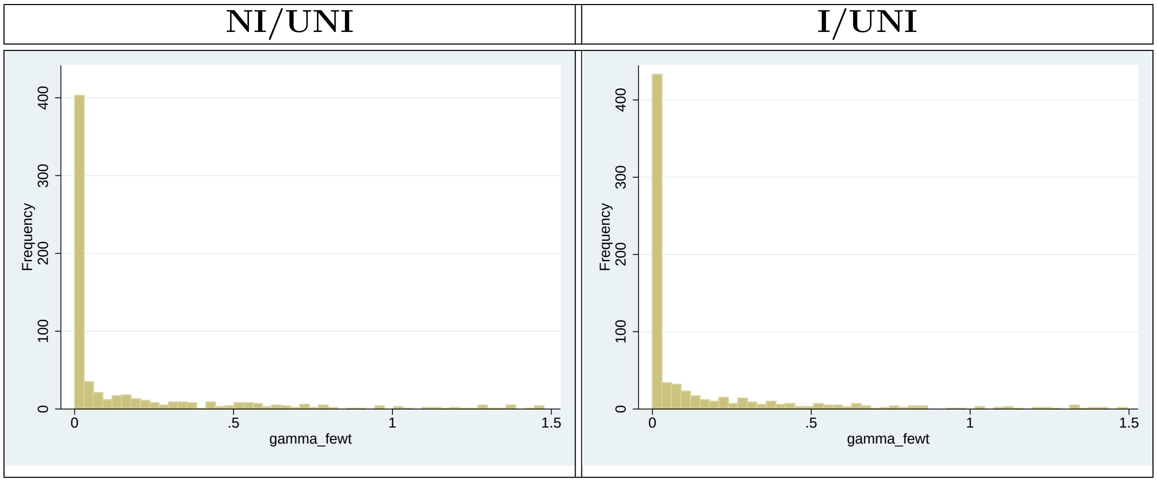


Figure 4.4: Histogram of γ_{it} - 2^{nd} Half

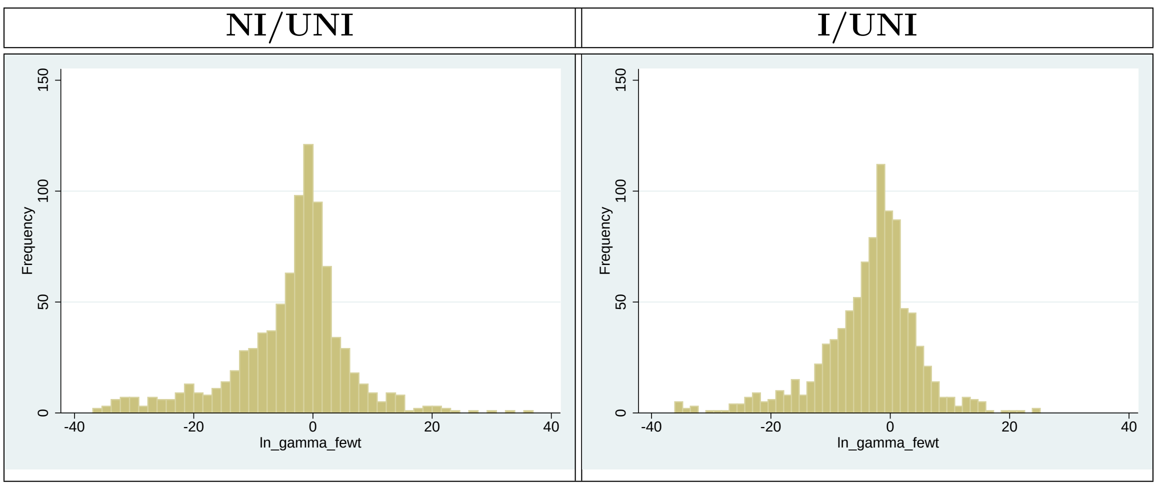


Figure 4.5: Histogram of ln (γ_{it}) - 2^{nd} Half

To understand the source of the heterogeneity in the γ_{it} values, we investigate how a buyer's cost ratio is influenced by the factors considered in the all-periods analysis. Since no extreme γ_{it} values[29] are observed in the second half of the game, we do not exclude any observations for this analysis. To control for the pair-level fixed effects, we conduct clustered fixed-effects regressions at the buyer-pair level, and present the results controlling for the time fixed effects.[30] The results are provided in Table 4.8.

[29]Based on the mean values for each individual and/or for each period.

[30]Consistent with our observations in the all-periods analysis, for all models, Hausman tests strongly reject the null hypothesis, indicating that fixed-effects models are more appropriate than random-effects models. Therefore, for both **NI/UNI** and **I/UNI** treatments, we report the results

Table 4.8: Clustered Regressions of ln (γ_{it}) - 2^{nd} Half with Time Fixed Effects

	ln (γ_{it})	
	NI/UNI	**I/UNI**
	All Observations	All Observations
$I_{i,t-2}$	-0.0939***	-0.0772***
	(0.01)	(0.01)
$B_{i,t-2}$	0.0799***	0.0737***
	(0.01)	(0.01)
$\mathcal{N}_{i,t-1}$	-0.0410***	-0.0534***
	(0.01)	(0.01)
$R_{i,t-1}$	-0.110***	-0.0936***
	(0.01)	(0.01)
$D_{i,t-1}$	0.104***	0.0993***
	(0.01)	(0.01)
N	897	960
R^2	0.640	0.740
# buyers	38	40

*** p<0.01, ** p<0.05, * p<0.1
Clustered standard errors are in parentheses.

Overall, the signs of the coefficients are consistent with those in the all-periods analysis. We observe that the differences in the coefficients between **NI/UNI** and **I/UNI** become insignificant in the second half of the game, which is expected due to learning over time and the system reaching steady-state.[31] Thus, consistent with our observations for supply line underweighting, *communication on the allocation policy significantly influences the buyers' perceived cost ratios in the initial periods, while the influence is reduced over time due to learning.*[32]

from fixed-effects models. We also focus on the models with time fixed effects. We provide the results from the models without time fixed effects in Table B.2 in Chapter 4 Appendices.

[31]The differences in the coefficients are not statistically significant for on-hand inventory, backlog, on-order quantity, and demand (with z-statistics 1.60, 0.54, 1.08, 0.31, respectively) and marginally significant for received shipment (with z-value of 1.73), in comparison to the z-critical, 1.65, at $\alpha = 0.1$ level.

[32]We also test for multi-collinearity for all four models in Table 4.8. We find that the maximum VIF for each model are 2.95 and 2.76, with mean VIF values of 2.07 and 2.08. As both maximum VIF values are considerably smaller than the rule of thumb of 10 (Kutner et al., 2004), we conclude that multi-collinearity is not a serious problem in these models.

4.4 Conclusion

In this chapter, we investigated buyers' ordering behavior under inventory competition for the limited capacity of a single supplier. We assumed that the supplier uses uniform allocation when the sum of the orders exceeds his available inventory. While most analytical studies based on economic theory and many empirical studies assume rational buyers who make optimal decisions, findings in behavioral literature find evidence of suboptimal decision making. For a closer examination of the buyer ordering behavior, we first compared the theoretical benchmark obtained from the simulations in the previous chapter with the actual buyer ordering decisions from our behavioral study. We found that the profit performances of buyers are significantly lower than the theoretical benchmark in the range of 0.8% to 14.1%.

To understand the buyer behavior better, we tested one of the observations reported in the literature, the supply line underweighting, using maximum likelihood estimation techniques. We showed that buyers underweight the supply line even when information on the allocation policy is communicated. We also showed that the effects of the state factors such as previous demand and inventory level (except for on-order quantity) are generally larger, when information on the allocation policy is not communicated. However, as the buyers' base-stock levels stabilize over time due to learning, the differences due to communication decrease.

In addition, using structural estimation modeling techniques, we estimated the buyers' perceived overage/underage cost ratios from the experiments. As compared to the true ratio of $\frac{1}{3}$, the estimated ratio under uniform allocation policy was 0.2836 with information and 0.3496 without information. Thus, the cost ratio with information disclosure seems to be slightly smaller than the original value (i.e., putting slightly more weight on the backlogging cost and less weight on the inventory holding cost), while without information disclosure slightly larger than the true value (i.e., putting relatively more weight on the inventory holding cost and less weight on the backlogging cost). We further examined the effect of various state factors on this cost ratio. Consistent with the findings for supply line underweighting, our analyses showed that when information on the allocation policy is not disclosed, the effect of the state factors on the perceived cost ratios is generally larger than the case with information. However, the differences in the coefficients between with vs. without information cases decrease over time.

As a future research direction, one can investigate whether information on the supplier's production policy can further change the buyers' ordering behavior (i.e., when buyers are also informed about the supplier's base-stock policy). Another future research direction is to develop behavioral models by incorporating the concept of psychological costs of overage and underage similar to Ho et al. (2010), and/or by considering the anchor selection models for decision-making (Gavirneni and Xia, 2009). Some potential anchors that could be considered are: (1) mean demand (i.e., mean demand anchoring tendency shown in Schweitzer and Cachon (2000)), (2) order forecast (i.e., soft orders that the buyer shares in advance), and (3) the optimal base-stock ordering level under 100% fill rate (i.e., with a fully reliable supplier).

Finally, while we assumed independent market demand for each buyer (i.e., no end-customer market competition) and a constant retail price (i.e., buyers as price takers), future research may consider demand competition between two buyers in the same end-customer market. As shown in analytical OM literature that demand competition may change the truth-inducing effect of uniform allocation on orders (Liu, 2012; Cho and Tang, 2014), while to the best of our knowledge, uniform allocation under demand competition has not been yet empirically studied, particularly in a behavioral context.

Chapter 5

Conclusion

In this dissertation, we investigated the buyers' forecasting and ordering behavior in a two-stage supply chain, particularly in the context of different capacity allocation policies and information disclosures of a supplier, using a behavioral framework.

In Chapter 2, we focused on the buyers' *order forecast* sharing behavior under different capacity allocation policies and information disclosures from the supplier. Our behavioral study showed that our proposed allocation policy, *forecast accuracy based allocation*, improves the accuracy of order forecasts submitted by the buyers, in comparison to *uniform allocation*, even without information disclosure on the allocation policy. The results also show that the order forecast accuracy further improves under both allocation policies, when the supplier allocation information is communicated to the buyers, which is more pronounced for uniform allocation. Our results also suggest that even without contractual obligations (which is mostly the case in practical settings such as semiconductor manufacturing), the buyers' forecast accuracy can be improved if the supplier rewards forecast accuracy in allocating inventory.

In the rest of the dissertation, we focused on the buyers' ordering behavior under uniform allocation. We first characterized a buyer's (static) optimal base stock level using analytical and numerical simulation approaches in Chapter 3. We then used the simulation results as a theoretical benchmark to compare against the buyer behavior observed in behavioral experiments in Chapter 4. Our results show that profit performances of buyers in the experiments are significantly lower than those of the simulated buyers in the range of 0.8% to 14.1%.

We then looked into the potential supply line underweighting of buyers, which is one of the behavioral causes of the bullwhip effect. Our results using maximum likelihood estimation showed that buyers underweight the supply line even when information on the allocation policy is communicated. We also found that in the initial periods, buyers tend to rely more on the previous period's demand when the supplier does not communicate his allocation policy to the buyers. However, as the decisions stabilize over time, the impact of communication on the various factors that affect buyers' ordering behavior becomes negligible.

To understand the buyers' ordering behavior better, we also looked into the perceived overage/underage cost ratios using structural estimation modeling techniques. Our results showed that buyers use inventory holding to backlog cost ratios quite close to the true value of the ratio, although they tend to emphasize the inventory holding cost more when they do not have any information on the allocation policy. In contrast, in the second half of the game, buyers tend to emphasize backlogging cost more than the inventory holding cost regardless of the information about the allocation policy. On the other hand, the effect of various state factors on the perceived cost ratios are generally larger when the information on the allocation policy is not communicated. Similar to our findings on supply line underweighting, we find that the impact of communication becomes negligible over time.

In this dissertation, in addition to academic contributions, our results provide insights for practitioners to understand buyers' strategic forecast sharing and ordering behavior and help with designing capacity allocation strategies.

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Appendix A

Chapter 2 Appendices

A.1 Outlier Analysis

For the statistical analysis of experiments, we removed "singles," i.e., subjects for which their partner's data could not be collected due to technical issues. We also removed two pairs from **1**, where one subject in each pair submitted consistently high order forecasts (5000 in one pair and 500-1000 in the other pair) for several periods causing high forecast inflation, not to bias our findings. This does not affect our findings in general, except for making the results on Hypotheses 1-2 stronger.

We used the average profit that the subjects made during the game as the main criterion for outlier detection since we observed a relatively tight profit range across subjects, particularly in the second half of the game. We utilized the minimum covariance determinant (MCD) estimator with 2.5% trimming (Verardi and Dehon, 2010). Table A.1 gives the list of the outlier subjects, and the average profit they made in each half of the game as well as across 50 periods (game profit). We identified three subjects (one each from $\mathbf{1}, \mathbf{3}, \mathbf{4}$) that met our criterion in both the first and second halves of the game. We removed the pairs of these subjects from the analysis of both halves of the game (marked with "X" in Table A.1). We identified three additional subjects (one each from **1**, **2**, and **3**) that qualified as outliers for only the first half of the game (marked with "Y" in Table A.1), so we excluded their pairs from the first half analysis not to bias the results. We present the average profit by subject after X and Y outliers are removed in Table A.2. We can see that the outliers that were removed from the first half analysis (Y) do not have a significant effect on the average profit in the second half and thus, we included them in the dataset for the second half analysis (our results continued to hold excluding them).

Finally, we identified periods with very high/low orders, which could bias mean forecast accuracy metrics by subject and pair. MCD estimator with 2.5% trimming detected the low (high) cutoff point for order quantity across 50 periods as 74 (340). This removed 95 (2.5%) observations from the second half of the game and 226 (5.9%) observations from the first half (the count of observations for the first half is before the "Y" outliers were removed). For robustness checks, we conducted all statistical tests once again including those outliers and we only spotted two changes in our results. The first change was observed for the forecast inflation difference between **2** vs. **4**, which was no longer significant ($p > 0.1$) at either subject or pair level. The second change was for the forecast error difference between **1** vs. **3**, which became significant ($p = 0.085$) only at the pair level. However, the rest of the results continued to hold.

Table A.1: Analysis of Outliers by Average Profit

Treatment	**Subject ID**	**Avg. 1^{st} half profit**	**Avg. 2^{nd} half profit**	**Avg. game profit**	**Removed from all analysis**	**Removed from 1^{st} half only**
1	A5B2	127.23	187.63	157.43		Y
1	A60B1	137.77	96.82	117.29	X	
2	B7B2	60.90	194.90	127.90		Y
3	E16B2	53.67	101.40	77.54	X	
3	E19B2	88.73	180.33	134.53		Y
4	D57B2	144.73	66.70	105.72	X	

A.2 Mann-Whitney Test Results for Order Forecast Accuracy Metrics

In this appendix, we present the full set of statistical (MW) test results at both subject and pair levels for all forecast accuracy metrics discussed in Section 2.4.2. In Table A.3, *z-stat* represents the MW test statistic, *p-value* is the statistical significance level

Table A.2: Average Profit across Subjects after Outliers are Removed

After removing the X outliers:

	1^{st} Half				**2^{nd} Half**			
N	$Mean$	$S.D.$	Min	Max	$Mean$	$S.D.$	Min	Max
156	176.37	16.09	60.90	195.12	187.12	6.43	162.68	200.04

After removing the Y outliers:

	1^{st} Half				**2^{nd} Half**			
N	$Mean$	$S.D.$	Min	Max	$Mean$	$S.D.$	Min	Max
150	178.06	10.27	145.72	195.12	187.24	6.32	162.68	200.04

and *p-order* is the probability that a randomly selected subject from the first group (the left of ">") has a higher forecast inflation/error than a randomly selected subject from the second group (the right of ">"). The notation "**13/24/12/34**" represents the pooled dataset of subjects from two treatments: **13** $>$ **24** investigates the effect of the implementation of an allocation policy regardless of whether the allocation policy is communicated or not, and **12** $>$ **34** investigates the effect of the communication of an allocation policy regardless of the allocation policy in effect. The bold entries are statistically significant at 0.1 level.

As it can be seen from this table, the tests are generally consistent at both levels. The only difference in the pairwise comparisons arises for mean absolute forecast error for **2** vs. **4**. While the statistical significance does not qualify at the 0.1 level at the subject level, the result is still significant at the pair level ($p = 0.0373$). However, the difference between **2** vs. **3** is not statistically significant at the subject or pair level for any of the forecast accuracy metrics.

Table A.3: MW Test Results for Order Forecast Accuracy Metrics

		Mean by subject			Mean by pair		
		z-stat	*p-value*	*p-order*	*z-stat*	*p-value*	*p-order*
Base forecast inflation (*base_inf*)							
	13>24	**2.740**	**0.0062**	**0.627**	**3.259**	**0.0011**	**0.714**
	12>34	1.245	0.2132	0.558	**1.879**	**0.0602**	**0.624**
	1>2	**1.675**	**0.0939**	**0.612**	**1.900**	**0.0574**	**0.681**
	1>4	**2.680**	**0.0074**	**0.679**	**3.654**	**0.0003**	**0.847**
	1>3	1.041	0.2980	0.569	1.374	0.1694	0.631
	2>4	1.011	0.3123	0.566	1.325	0.1850	0.623
	2>3	-1.073	0.2832	0.430	-0.893	0.3720	0.417
	3>4	**2.335**	**0.0195**	**0.652**	**2.786**	**0.0053**	**0.757**
Mean forecast inflation (*m_inf*)							
	13>24	**2.831**	**0.0046**	**0.631**	**2.799**	**0.0051**	**0.684**
	12>34	**2.507**	**0.0122**	**0.616**	**2.589**	**0.0096**	**0.670**
	1>2	**2.231**	**0.0256**	**0.649**	**1.842**	**0.0655**	**0.675**
	1>4	**3.761**	**0.0002**	**0.751**	**3.684**	**0.0002**	**0.850**
	1>3	**2.070**	**0.0384**	**0.638**	**2.046**	**0.0407**	**0.694**
	2>4	**1.665**	**0.0960**	**0.608**	**1.812**	**0.0699**	**0.667**
	2>3	-0.255	0.7987	0.483	-0.108	0.9138	0.490
	3>4	**1.886**	**0.0593**	**0.623**	**2.353**	**0.0186**	**0.718**
Mean forecast error (*m_fe*)							
	13>24	**3.097**	**0.0020**	**0.644**	**3.209**	**0.0013**	**0.711**
	12>34	1.564	0.1179	0.573	1.529	0.1261	0.601
	1>2	**1.717**	**0.0861**	**0.615**	**1.754**	**0.0794**	**0.667**
	1>4	**3.085**	**0.0020**	**0.706**	**3.274**	**0.0011**	**0.811**
	1>3	1.020	0.3080	0.568	1.082	0.2794	0.603
	2>4	1.578	0.1145	0.603	1.298	0.1941	0.620
	2>3	-1.131	0.2582	0.427	-1.190	0.2340	0.390
	3>4	**2.834**	**0.0046**	**0.684**	**2.840**	**0.0045**	**0.762**
Mean absolute forecast error (*ma_fe*)							
	13>24	**1.876**	**0.0607**	**0.587**	1.579	0.1142	0.604
	12>34	**2.399**	**0.0165**	**0.611**	**2.829**	**0.0047**	**0.686**
	1>2	1.592	0.1115	0.606	1.052	0.2926	0.600
	1>4	**2.986**	**0.0028**	**0.699**	**3.040**	**0.0024**	**0.789**
	1>3	**2.257**	**0.0240**	**0.651**	**2.193**	**0.0283**	**0.708**
	2>4	1.386	0.1658	0.590	**2.083**	**0.0373**	**0.693**
	2>3	0.274	0.7839	0.518	0.730	0.4652	0.568
	3>4	1.131	0.2582	0.573	1.217	0.2235	0.613

A.3 Analysis of the First Half of the Game

In this section, we provide our analysis for the first 25 periods of the game. Table A.4 gives the design matrix with updated number of subjects ($N = 150$), after excluding the outliers for the first half analysis:

Table A.4: Experimental Design

	Implementation	
Information	**UNI**	**FCT**
NI	**1** (34)	**2** (38)
I	**3** (38)	**4** (40)

Descriptive statistics on the order quantity, forecast, and forecast accuracy metrics by treatment are given in Table A.5. We observe that the order quantities in the first half of the game are higher compared to the second half, but are still similar across treatments. The median order forecasts and base forecast inflation are relatively higher in the first half of the game for all treatments except **1**, where there is no significant change over the course of the game. Order forecasts are again statistically significantly higher than the mean of the consumer demand distribution, 200 ($p < 0.001$). Analyzing the forecast error with respect to firm orders closely, we observe over-reporting behavior in 56% of the subjects ($m\_fe > 0$, $Mean = 10.7$, $S.D. = 10.6$), and under-reporting behavior in 44% of the subjects ($m\_fe < 0$, $Mean = -10.6$, $S.D. = 9.5$). Thus, while order forecast inflation is still persistent in the first half, we find that negative errors are of a higher concern than the second half (recall 83% vs. 17%). This is not surprising as subjects may be exploring the effects of their orders and forecasts in the early phases of the game. However, it is interesting to see that the tendency moves towards inflation in the second half once the game stabilizes.

We next compare the order forecast accuracy metrics by treatment. We use the nonparametric MW test for all our statistical comparisons at the subject level unless otherwise stated.

Table A.5: The Effect of Allocation Policy on Buyers' Order Forecast Accuracy (1^{st} half)

	NI/UNI	NI/FCT	I/UNI	I/FCT
	1	**2**	**3**	**4**
N	34	38	38	40
$\bar{O}$	210.1 (9.6) [207.7]	211.9 (12.1) [209.8]	210.1 (8.6) [207.9]	210.7 (8.3) [207.5]
$\bar{F}$	214.8 (16.3) [210.8]	213.2 (17.5) [211.0]	213.4 (12.1) [212.7]	207.3 (6.8) [206.0]
$base\_inf$	7% (8%) [5%]	7% (9%) [5%]	7% (6%) [6%]	4% (3%) [3%]
m_fe	4.7 (17.1) [1.8]	1.3 (16.8) [1.5]	3.3 (13.5) [2.8]	-3.4 (9.7) [-1.4]
ma_fe	46.5 (16.8) [44.2]	43.8 (16.6) [44.0]	39.5 (15.2) [37.8]	36.6 (16.6) [38.5]
m_inf	25.6 (13.0) [20.6]	22.5 (11.7) [20.0]	21.4 (10.9) [17.9]	16.6 (8.6) [16.0]

Note. Standard deviations are given in parentheses. Median values are given in brackets. $\bar{O}$ is the average order quantity and $\bar{F}$ is the average order forecast across subjects.

- The mean order forecast error/bias (m_fe) under **4** is statistically significantly lower than other treatments.[1] Interestingly, in contrast to the positive bias that we observed in the second half of the game, we see a negative bias under **4** in the first half. We compare the absolute value of this bias to understand whether it is statistically lower in magnitude than other treatments, which we confirm against the **UNI** treatments ($p < 0.05$). Thus, even though we observe predominantly under-reporting behavior in the first half of the game when **FCT** is implemented with communication, the order forecast error is still lower in magnitude than **UNI** treatments.

- The mean absolute order forecast error (ma_fe) is reduced for both **FCT** and **UNI** when implemented with communication ($p < 0.1$). Similar to the second half results, the difference between **3** vs. **4** is not statistically significant.

- When **FCT** is implemented with communication (**4**), the mean order forecast inflation (m_inf) is reduced compared to all other treatments.[2]

- Similar to the second half results, although **4** dominates over **1** in mean order forecast error, absolute error and inflation ($p < 0.05$), the difference between **2** vs. **3** is not statistically significant at 0.1 level for any forecast accuracy metrics. That is, **UNI** with communication seems to have similar performance with **FCT** without communication also in the first half of the game.

In summary, our analysis from the first half of the game also confirms that buyers' order forecast accuracy can be improved when **FCT** is implemented with communication. In particular, the most significant reduction in order forecast inflation and bias is observed under **4** against other treatments. That is, communication is critical

[1]For **1** vs. **4** and **3** vs. **4**, $p < 0.05$. For **2** vs. **4**, $p < 0.10$ (0.05) at the subject (pair) level.

[2]**1** vs. **4**, $p = 0.004$; **2** vs. **4**, $p = 0.025$; **3** vs. **4**, $p = 0.089$.

for **FCT** to be effective, particularly in the first half of the game. This is intuitive as subjects would be more motivated to submit accurate order forecasts from the start if they are informed about the rewarding mechanism.

A.4 List of Experiment Sessions

Table A.6 presents the list of experiment sessions that we conducted to collect our dataset. Each cell gives the number of subjects that played in a particular treatment in each session (after singles/outliers are removed as described in Appendix A.1). Note that all sessions in 2011 and later were administered by the same experimenter. Thus, while the data was collected over multiple sessions, we do not expect any bias in the subjects' understanding of the game due to experimenter differences in presenting the instructions.

Table A.6: List of Experiment Sessions

Sep-Nov 2009			**Apr-Nov 2010**			**9/28/2011**		
	UNI	**FCT**		**UNI**	**FCT**		**UNI**	**FCT**
NI	10		**NI**		18	**NI**	2	
I			**I**		4	**I**		6
10/14/2011			**4/10/2013**			**4/18/2014**		
	UNI	**FCT**		**UNI**	**FCT**		**UNI**	**FCT**
NI	2	2	**NI**			**NI**		
I		4	**I**		6	**I**	4	
4/25/2014			**5/2/2014**			**5/12/2014**		
	UNI	**FCT**		**UNI**	**FCT**		**UNI**	**FCT**
NI	4		**NI**	2		**NI**		
I	6		**I**	2		**I**	8	
11/30/2015			**12/4/2015**			**12/9/2015**		
	UNI	**FCT**		**UNI**	**FCT**		**UNI**	**FCT**
NI	6	6	**NI**			**NI**		
I			**I**		4	**I**	4	4
2/26/2016			**3/4/2016**			**3/25/2016**		
	UNI	**FCT**		**UNI**	**FCT**		**UNI**	**FCT**
NI		4	**NI**	6	6	**NI**	4	4
I		4	**I**	6	8	**I**	10	

A.5 Simulation Game Screenshots

The main game screen for each buyer displays the state of the system at the beginning of the current period, right before placing an order. The player can enter the order for the current period, revise the existing forecasts for the next three periods and enter a new forecast for the fourth period in the future (rolling horizon forecasting). Various key metrics are displayed to help with the decision making process. These include performance measures such as the average per period profit, supplier's overall fill rate, the buyer's overall service level to consumers, exponentially smoothed forecast accuracy, as well as metrics to help with understanding the system state at the end of the previous period such as received shipment from the supplier, realized consumer demand, on-order quantity which the supplier has yet to send in future periods, ending inventory, and backlog levels. The player can click on the 'Parameters' tab to view the revenue/cost parameters, 'Financials' tab to see a detailed history of key metrics, 'Forecast History' tab to see a history of forecasts and the associated forecast accuracy, 'Graphical Display' tab to see a graphical representation of key metrics over time, and the 'Comments' tab to enter any comments during the game.

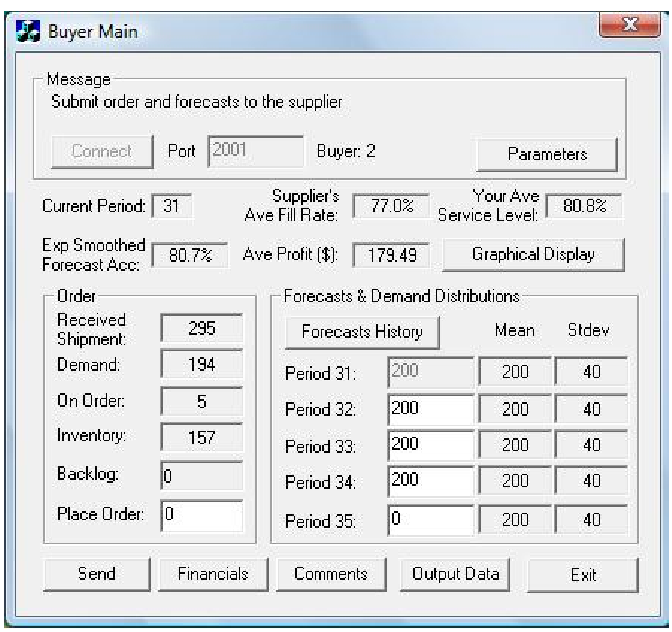
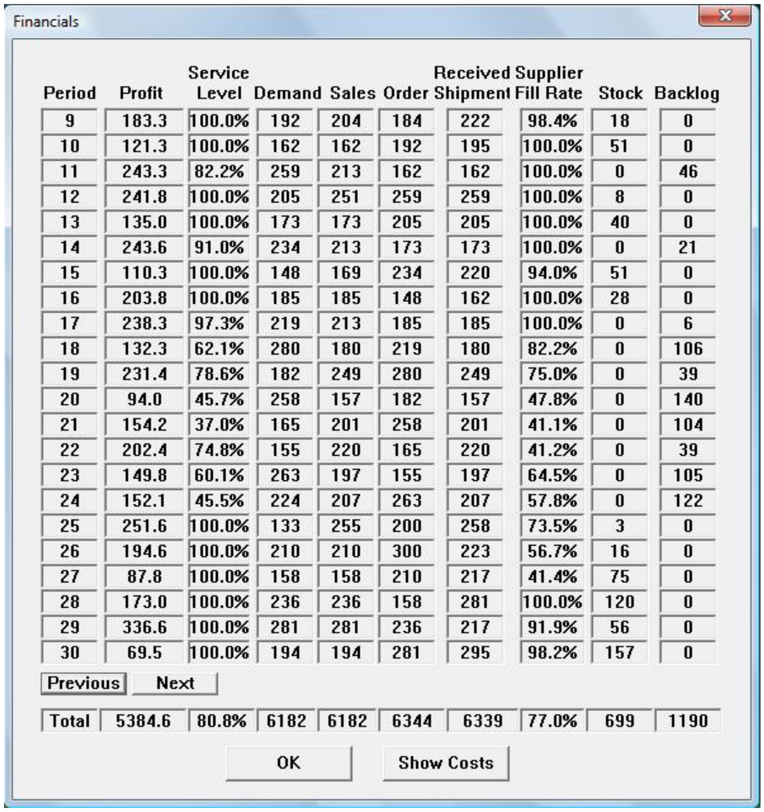


Figure A.1: Buyer Main Screen

Financials Screen displays a detailed history of the key metrics up to the current period. For each period, these metrics include the profit, service level to consumers, realized consumer demand, sales quantity, the amount ordered and received from the supplier, supplier's fill rate, the ending inventory, and backlog levels.



Financials

Period	Profit	Service Level	Demand	Sales	Order	Received Shipment	Supplier Fill Rate	Stock	Backlog
9	183.3	100.0%	192	204	184	222	98.4%	18	0
10	121.3	100.0%	162	162	192	195	100.0%	51	0
11	243.3	82.2%	259	213	162	162	100.0%	0	46
12	241.8	100.0%	205	251	259	259	100.0%	8	0
13	135.0	100.0%	173	173	205	205	100.0%	40	0
14	243.6	91.0%	234	213	173	173	100.0%	0	21
15	110.3	100.0%	148	169	234	220	94.0%	51	0
16	203.8	100.0%	185	185	148	162	100.0%	28	0
17	238.3	97.3%	219	213	185	185	100.0%	0	6
18	132.3	62.1%	280	180	219	180	82.2%	0	106
19	231.4	78.6%	182	249	280	249	75.0%	0	39
20	94.0	45.7%	258	157	182	157	47.8%	0	140
21	154.2	37.0%	165	201	258	201	41.1%	0	104
22	202.4	74.8%	155	220	165	220	41.2%	0	39
23	149.8	60.1%	263	197	155	197	64.5%	0	105
24	152.1	45.5%	224	207	263	207	57.8%	0	122
25	251.6	100.0%	133	255	200	258	73.5%	3	0
26	194.6	100.0%	210	210	300	223	56.7%	16	0
27	87.8	100.0%	158	158	210	217	41.4%	75	0
28	173.0	100.0%	236	236	158	281	100.0%	120	0
29	336.6	100.0%	281	281	236	217	91.9%	56	0
30	69.5	100.0%	194	194	281	295	98.2%	157	0
Total	5384.6	80.8%	6182	6182	6344	6339	77.0%	699	1190

Previous Next

OK Show Costs

Figure A.2: Buyer Financials Screen

Graphical Display Screen displays a graphical representation of key metrics over time up to the current period. The player can select which metrics to display.

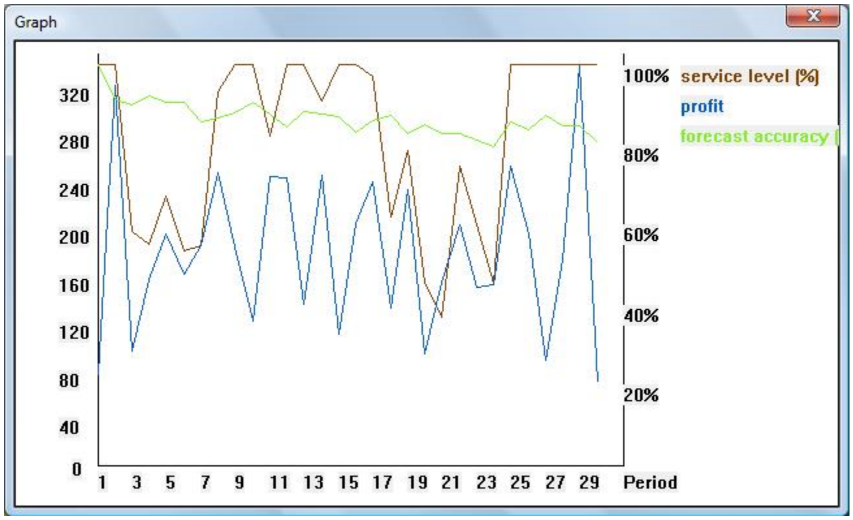
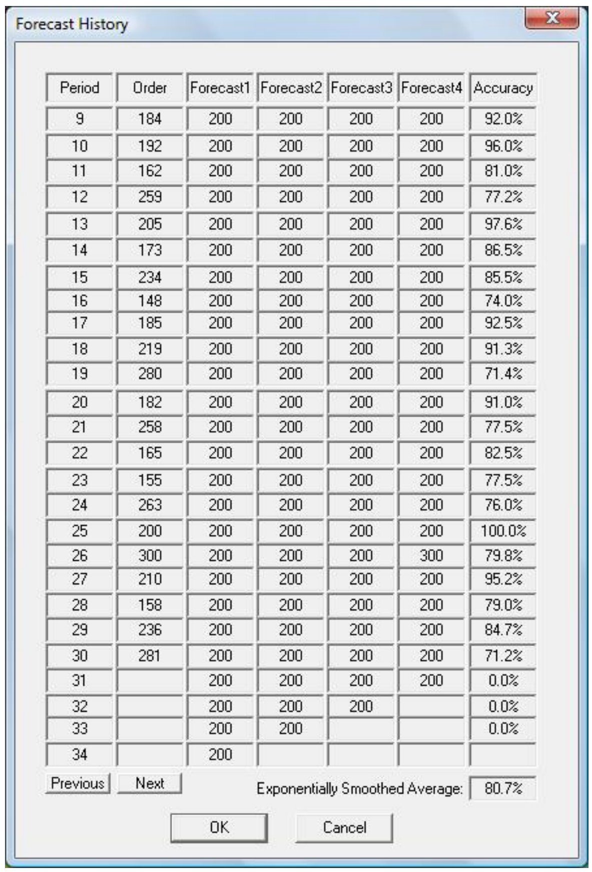


Figure A.3: Buyer Graphical Display Screen

Forecast History Screen provides a detailed history of the forecasts, orders, and associated exponentially smoothed forecast accuracy up to the current period. As an example of the forecast accuracy computations in Chapter 2, the 'Accuracy' numbers for each period that appear in the Forecast History screen in Figure A.4 correspond to fa_{it}, while the 'Exponentially Smoothed Average' number, 80.7%, corresponds to FA_{it} as of period 30. The latter number also appears in the Buyer Main screen as it can be seen in Figure A.1.



Forecast History

Period	Order	Forecast1	Forecast2	Forecast3	Forecast4	Accuracy
9	184	200	200	200	200	92.0%
10	192	200	200	200	200	96.0%
11	162	200	200	200	200	81.0%
12	259	200	200	200	200	77.2%
13	205	200	200	200	200	97.6%
14	173	200	200	200	200	86.5%
15	234	200	200	200	200	85.5%
16	148	200	200	200	200	74.0%
17	185	200	200	200	200	92.5%
18	219	200	200	200	200	91.3%
19	280	200	200	200	200	71.4%
20	182	200	200	200	200	91.0%
21	258	200	200	200	200	77.5%
22	165	200	200	200	200	82.5%
23	155	200	200	200	200	77.5%
24	263	200	200	200	200	76.0%
25	200	200	200	200	200	100.0%
26	300	200	200	200	300	79.8%
27	210	200	200	200	200	95.2%
28	158	200	200	200	200	79.0%
29	236	200	200	200	200	84.7%
30	281	200	200	200	200	71.2%
31		200	200	200	200	0.0%
32		200	200	200		0.0%
33		200	200			0.0%
34		200				

Previous Next Exponentially Smoothed Average: 80.7%

OK Cancel

Figure A.4: Buyer Forecast History Screen

A.6 Simulation Game Session Player Quiz

After we provided the necessary background information about the supply chain game to the players at the beginning of each game session, and showed the game screens presented in the previous section, we gave them a verbal quiz (see Figure A.5). Only after we received the correct answers and clarified their questions, we started the game session. For example, we explained that the consumer demand that a buyer faced was normally distributed with a mean of 200 and a standard deviation of 40. In the quiz, we ensured that they understood that there was no correlation between consecutive demand realizations, and the demand they faced was independent from their partner's.

Quiz

1. You play with the same partner (competitor) throughout the experiment?
2. Both you and your competitor purchase from the same supplier?
3. The supplier is played by a computer?
4. The amount of products you receive from the supplier in a period could be affected by the order that your competitor places with the supplier in the same period?
5. How is your profit calculated in each period?
6. Suppose the demands that you had in the first 5 periods were 210, 220, 230, 240, and 250 respectively. What is the demand for the 6th period going to be?

Quiz (Cont'd)

Suppose you order 100 units in period 31 and received 105 units. The demand for period 31 turns out to be 200.

What are the values of the following fields at the beginning of period 32?

- Received shipment
- Demand
- On Order
- Inventory
- Backlog

Figure A.5: Preliminary Game Quiz

Appendix B

Chapter 4 Appendices

B.1 Summary of Results without Time Fixed Effects

We provide the results without time fixed effect controlled in Table B.1 below.

Table B.1: Clustered Regressions of ln (γ_{it}) under **NI/UNI** and **I/UNI** - All Periods without Time Fixed Effects

	ln (γ_{it})			
	NI/UNI		**I/UNI**	
	All Observations	Without Extremes	All Observations	Without Extremes
$I_{i,t-2}$	-0.133***	-0.0968***	-0.103***	-0.0840***
	(0.01)	(0.01)	(0.01)	(0.01)
$B_{i,t-2}$	0.151***	0.0769***	0.0867***	0.0639***
	(0.02)	(0.01)	(0.01)	(0.01)
$\mathcal{N}_{i,t-1}$	-0.0497***	-0.0345***	-0.0134*	-0.0116*
	(0.01)	(0.00)	(0.01)	(0.01)
$R_{i,t-1}$	-0.148***	-0.0900***	-0.113***	-0.0885***
	(0.01)	(0.01)	(0.01)	(0.01)
$D_{i,t-1}$	0.186***	0.132***	0.166***	0.133***
	(0.01)	(0.01)	(0.01)	(0.01)
N	1,708	1,454	1,805	1,621
R^2	0.571	0.562	0.610	0.559
# buyers	38	38	40	40

*** p<0.01, ** p<0.05, * p<0.1
Clustered standard errors are in parentheses.

As in Chapter 4, we compared the coefficients of the independent variables using z-tests, and obtained similar results. With all observations, the differences in the coefficients of on-hand inventory, backlog, on-order quantity, received shipment, and demand are all statistically significant (with z-statistics of 2.70, 4.28, 3.73, 2.29, 2.25, respectively), in comparison to the z-critical, 1.96, at $\alpha = 0.05$ level. On the other hand, without extreme values, the differences in the coefficients of on-hand inventory, backlog, received shipment, and demand become insignificant, while the difference in the coefficients of on-order quantity remained statistically significant.

We also show the results from analysis with the 2nd half periods in Table B.2.

Table B.2: Clustered Regressions of ln (γ_{it}) under **NI/UNI** and **I/UNI** - 2^{nd} Half without Time Fixed Effects

	ln (γ_{it})	
	NI/UNI	**I/UNI**
	All Observations	All Observations
$I_{i,t-2}$	-0.105***	-0.0971***
	(0.01)	(0.01)
$B_{i,t-2}$	0.0772***	0.0785***
	(0.01)	(0.01)
$\mathcal{N}_{i,t-1}$	-0.0363***	-0.0442***
	(0.01)	(0.01)
$R_{i,t-1}$	-0.105***	-0.0971***
	(0.01)	(0.01)
$D_{i,t-1}$	0.152***	0.157***
	(0.01)	(0.01)
N	897	960
R^2	0.560	0.635
# buyers	38	40

*** p<0.01, ** p<0.05, * p<0.1
Clustered standard errors are in parentheses.

Similar to the results in Chapter 4, the differences in the coefficients of on-hand inventory, backlog, on-order quantity, received shipment, and demand are not statistically significant (with z-statistics of 0.82, 0.10, 0.80, 0.86, 0.45, respectively), in comparison to the z-critical, 1.65, at $\alpha = 0.1$ level.