EXPERIMENTS ON SUPPLY CHAIN CONTRACTING: EFFECTS OF CONTRACT TYPE AND RELATIONSHIP LENGTH

by

NÜKTE ŞAHİN

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APPROVED BY:

Asst. Prof. Dr. Murat Kaya ....
(Thesis Supervisor)

Assoc. Prof. Dr. Can Akkan ....

Assoc. Prof. Dr. Bülent Çatay ....

Asst. Prof. Dr. Çağrı Haksöz ....

Assoc. Prof. Dr. Tonguç Ünlüyurt ....

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Nükte Şahin

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Abstract

In this thesis, we conduct experiments with human decision makers on supply chain contracting. We consider a manufacturer-retailer supply chain where the manufacturer sets contract parameters and the retailer faces the newsvendor problem. Contrary to theoretical predictions, we find the experimental performance of the wholesale price contract and the buyback contract to be close to each other. The buyback contract fails to fulfill its promise of inducing high order quantities leading to higher supply chain profits. The manufacturers offer more profitable buyback contracts to retailers, and as a result, the retailers make higher profit and the manufacturers make lower profit than predicted. On the contrary, the simple wholesale price contract resulted in higher retailer and total supply chain profits than predicted, thanks to the overstocking bias of the retailers. Another surprising observation is that experiments with short-run interaction between the manufacturer-retailer pairs resulted in higher profit than the experiments with long-run interaction. Finally, we did not find consistent evidence to support the existence of learning-by-doing, and of certain decision heuristics mentioned in literature.

TEDARİK ZİNCİRİ SÖZLEŞMELERİNDE DENEYLER:
SÖZLEŞME TİPLERİ VE İLİŞKİ UZUNLUĞUNUN ETKİLERİ

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Anahtar Kelimeler: tedarik zinciri yönetimi, sözleşme, satılmayan malların geri alımı üzerinden sözleşme, toptan satış fiyatı üzerinden sözleşme, davranışsal operasyon, deney, kararlarda yanlılık

Özet

Bu tezde, tedarik zincirlerinde sözleşmeler konusunda gerçek insanlarla karar verme deneyleri gerçekleştirdik. Üreticinin sözleşmeyi önerdiği, perakendecinin de "gazeteci çocuk" problemi ile karşı karşıya kaldığı bir üretici-perakendeci tedarik zincirini ele aldık. Kuramsal tahminlerin aksine, "satılmayan malların geri alımı üzerinden sözleşme" ile "toptan satış fiyatı üzerinden sözleşme" `nin deneysel performanslarının farklı olmadığını bulduk. Geri alım sözleşmesinin, perakendecinin stok miktarını arttırarak toplam karı yükseltme beklentisini karşılayamadığını gözlemledik. Üreticilerin perakendecilere beklenenden daha karlı geri alım sözleşmeleri önermesi sonucu perakendeci karı artarken üretici karı beklenenden ciddi derecede daha düşük gerçekleşti. Toptan satış fiyatı üzerinden sözleşme ise, perakendecilerin fazla mal stoklaması sonucu beklenenden daha yüksek perakendeci ve tedarik zinciri karına yol açtı. Bir diğer önemli sonuç ise beklentilerin aksine, üretici-perakendeci ilişkisinin kısa vadeli olduğu deneylerde, uzun vadeli deneylere göre daha yüksek tedarik zinciri karı elde edilmesi oldu. Son olarak, deneklerin zamanla daha iyi kararlar vermeyi öğrendiklerine ve literatürde bahsedilen karar sezgisellerini kullandıklarına yönelik destek bulamadık.

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CHAPTER 1

1. INTRODUCTION

Supply chains consist of individual firms, each aiming to maximize its own profit. It is well documented that the pursuit of individual profit maximization leads to suboptimal solutions from the supply chain point of view. This is why the study of contracts between supply chain members has attracted great attention in business as well as in academic literature. A well crafted contract can align the incentives of the individual firms, leading to higher overall efficiency and higher gains for all parties, including the end-consumers. More than simply a pricing agreement, the contract is a tool to share profits, risks and information.

Supply chain contracting and coordination literature has studied many different types of contracts and produced a wealth of analytical models (Cachon, 2003; Kaya and Ozer, 2011). All of these models are based on a number of behavioral assumptions regarding how people make decisions (rational decision makers who aim to maximize their expected utility) and how people strategically interact (game-theoretic equilibrium concepts). While widely used in modeling, experimental economists have been challenging these assumptions through controlled experiments with human decision makers (Kagel and Roth 1995). These studies have uncovered significant differences between human decisions and the predictions of analytical models, and human behavior. Hence, it would be important to test the assumptions and predictions of analytical models through using such experiments before making managerial recommendations. This is particularly important for areas where “field studies” would be extremely difficult to conduct, such as supply chain contacting. Experiments uncover the gaps between theoretical predictions and human decisions, allowing the development of better analytical models that have higher explanatory and predictory prediction power. This approach may help bridge the long standing gap between operations management practice and research.

In this study, we consider the simplest supply chain involving inventory risk and contracting: A manufacturer-retailer supply chain where the retailer faces stochastic consumer demand. The manufacturer moves first by offering a contract to the retailer. If the retailer accepts the contract, she determines how much to order from the manufacturer and stock prior to the selling season. This is the only ordering opportunity for the retailer, making her problem a "newsvendor problem".

We consider two different contracts between the firms. (1) *Wholesale price contract (w)* where the wholesale price is w. This is the simplest possible contract where the retailer pays the wholesale price w per unit she buys. She cannot return unsold units to the manufacturer. According to the analytical solution, this contract causes the retailer to order less than the supply-chain-optimal stock quantity. This leads to inefficiency in the supply chain. *(2) Buyback contract (w,b)* where the manufacturer charges a wholesale price w, and buys back unsold units at a buyback price b. According to the analytical solution, this contract can coordinate the supply chain with the proper choice of contract parameters (w,b).

We chose the buyback contract because it is easy to understand and provides a nice setting to study risk and profit sharing between firms. In addition, buyback contracts are widely used in industries such as publishing, pharmaceuticals and computer software and hardware (Padmanabhan and Png 1995, Wang and Webster 2009). Around 30% of new hardcover books are returned to the publishers by booksellers (Chopra and Meindl 2007). Electronics manufacturers such as Intel provide returns policies to their distributors (Wang and Webster 2009).

We aim to answer the following research questions:

- *How is the experimental performance of the contracts compare to the predictions of the analytical models?* In a similar study, Keser and Paleologo (2004) observed that the overall efficiency wholesale price contract is close to the predicted value; however, the profit is more equitably shared between the firms than predicted. We extend their work by studying the buyback contract in addition to the wholesale price contract.

- *How do the experimental performances of buyback and wholesale price contracts compare with each other?* Theory suggests that the buyback contract should outperform the wholesale price contract. In particular, the buyback contract is predicted to induce higher stock quantities from the retailer, leading to higher supply chain profits.

- *How does the length of relationship between subjects affect the results?* One expects that in a longer-run relationship, firms learn about each other and may develop cooperation over time. At the same time, a long-run relationship runs the risk of firms engaging in strategic moves in the early periods to signal “toughness”.

- *What factors do retailers consider in setting stock quantities?* At the heart of our model is the retailer’s newsvendor decision. The manufacturer manipulates this decision through contract parameters he proposes. Numerous researchers have showed that people do not choose the newsvendor quantity in experiments. Decision makers are affected by irrelevant information, and resort to decision heuristics. We would like to understand what factors the retailer subjects consider in their stock quantity decisions. This has implications for contract design.

- *Do subjects learn to make better decisions over time?* We would like to understand if and how the subjects’ decisions change over time due to learning-by-doing.

The rest of this thesis is organized as follows. In Chapter 2, we summarize the related literature. In Chapter 3, we provide information on the analytical background of our problem. In Chapter 4, we explain our experimental setting and procedures. In Chapter 5, we compare overall results of buyback contract experiments and wholesale price contract experiments, and we explain the individual experiments in detail. In Chapter 6, we discuss the decision heuristics. In Chapter 7, we conclude with discussions and future research suggestions.

CHAPTER 2

2. LITERATURE SURVEY

2.1. The Newsvendor Model

The analytical model we consider revolves around the retailer's newsvendor problem, and how the manufacturer can manipulate this problem through the choice of the contract parameters. The newsvendor problem, introduced by Arrow et al. (1951), is a fundamental building block in stochastic inventory theory (see for example, Petruzzi and Dada 1999, Khouja 1999, Porteus 2002). Arrow et al. came up with the famous "critical ratio" solution to the problem, capturing the fundamental trade-off between ordering too much and ordering too little relative to demand realization. The original model is about a newsvendor that needs to determine how many copies of a newspaper to order and stock at the beginning of a day, to meet stochastic demand during the day. However, the model is relevant to many different problem settings including inventory and capacity decisions in fashion and electronics industries; capacity management in service industries such as the airlines and hotels (Weatherford and Pfeifer 1994); and individual health care and insurance purchasing (Rosenfield 1986, Eeckhoudt et al. 1991).

Thanks to its simple and elegant nature, the newsvendor model has been used extensively in the development of more complicated stochastic inventory models. However, empirical studies indicate that managers do not necessarily follow the newsvendor solution in relevant problem settings. For example, Fisher and Raman (1996) report the case of a fashion company (Sport Obermeyer) that does not use the newsvendor model in order quantity decisions. Corbett and Fransoo (2007)'s survey shows that small businesses do partially follow the newsvendor logic for high-margin products but not for their best-selling products.

The newsvendor model, similar to any analytical model of human decision making, is based on a number of behavioral assumptions regarding how people make decisions. Human beings are assumed to be rational decision makers that aim to maximize expected profit level. However, a number of experimental studies involving human decision makers consistently found biases (i.e., observed systematic deviations in decision making) between theoretical predictions and subject decisions. Economists have been using such controlled laboratory experiments to study human decision making for a long time (see, for example, Kagel and Roth 1995). In fact, Daniel Kahneman and Vernon Smith co-received the Nobel Prize in Economic Sciences for their pioneering work in experimental/behavioral economics. The use of experimental/behavioral methods in operations management has increased rapidly in the last years, leading to the emergence of the "behavioral operations management" field (see Bendoly et al. 2006, Gino and Pisano 2008).

Schweitzer and Cachon (2000) conducted the first laboratory study of the newsvendor problem. These authors show that newsvendors (retailers) overorder for a low profit margin product, whereas they underorder for a high profit margin product. The authors show that this " pull to center effect" cannot be explained by risk preferences, prospect theory preferences, loss aversion, waste aversion, stockout aversion or an underestimation of opportunity costs. The authors offer the following three heuristics to explain their findings:

- Mean anchor heuristic: The retailer anchors its decision on mean demand and then adjusts towards the optimal order quantity.
- Chasing demand heuristic: The decision maker anchors on the previous order quantity and adjust toward the most recent demand observation.
- Minimize ex-post inventory error: The decision maker regrets from not having ordered the realized demand, although it was not the optimal decision ex-ante.

The first two are related to the "anchoring and insufficient adjustment" type heuristics where (Kahneman et al. 1982) people anchor their decisions around some available but irrelevant information, and insufficiently adjust around this value over time.

Bolton and Katok (2008) also observe the pull to center effect in their experiments. They show that the retailers' order decisions can be improved through learning from experience, and by restricting them to place long-standing (10-periods) orders. Benzion et al. (2008) study different demand distributions and show that the previous-period bias is weakened over time. Bostian et al. (2008) show that the pull-to-center effect can be explained by an adaptive learning model where the subjects learn about the attractiveness of each order quantity alternative over time based on their past experience (EWA model). Lurie and Swaminathan (2009) find that more frequent feedback does not necessarily improve newsvendor performance.

Researchers have identified a number of "decision biases" to explain deviations from the optimal newsvendor quantity:

- **Different utility functions:** The newsvendor model assumes that the decision maker's objective is to maximize his expected profit. However, experimental studies have identified other utility functions. These are related to the Prospect Theory of Kahneman and Tversky (1979).

    - **Risk aversion**: Eeckhoudt et al. (1995) show analytically that a risk-averse newsvendor will order less than a risk-neutral one. Prospect theory (Kahneman and Tversky 1979) predicts that people act risk averse in the domain of gains, but risk-seeking in the domain of losses (reflection effect). Corbett and Fransoo (2007)'s survey results confirm this prediction for small business owners facing newsvendor problems.

    - **Loss aversion** (Kahneman and Tversky 1974). People are more averse to losses than they like same-sized gains. Wang and Webster (2006) show analytically that a loss-averse newsvendor will order less than a risk-neutral newsvendor when the shortage cost is low.

    - **Framing:** People's decisions are affected by the way the problem is presented (Tversky and Kahneman 1984). Schultz et al. (2007) compare the newsvendor results under a positive frame that highlights profit, and a negative one that highlights costs. To their surprise, experiments indicate no significant difference. Ho and Zhang (2008) illustrate the effect of framing in the supply chain contracting domain.

- **Bounded rationality:** Standard economic theory assumes that people rationally choose the "best response" among alternatives. However, in practice, people make noisy decisions. They may make calculation or recording errors due to limited cognitive ability, limited memory and attention span. When faced with complex decision situations, people may resort to decision heuristics as shortcuts. Su (2008) generalizes the newsvendor model to account for bounded rationality using a quantal response equilibrium (QRE) framework. This framework acknowledges that people do not always make the best decision, but good decisions have a higher probability of being made than worse ones. Gavirneni and Isen (2008) record and analyze the thought process of newsvendor subjects in experiments. They find that most subjects correctly identified the overage and underage costs, but failed to convert this into the optimal order quantity. This finding suggests that the newsvendor problem may not be as intuitive as thought by researchers.

- **Irrational behavior:** Becker-Peth et al. (2009) analyze how subjects respond to different parameters of the buyback contract, and use experiment data to generate response functions to estimate the mean orders, order variances and expected profits. The authors show that although the newsvendor subjects act irrationally, their decisions can be predicted very accurately using these response functions.

- **Overconfidence:** Croson et al. (2008) show that newsvendor subjects have a biased belief that the demand distribution has a lower variance than its true variance. The authors show that this overconfidence bias leads to suboptimal order quantities, and they develop incentive contracts to induce optimal newsvendor quantities.

- **Cultural differences:** Feng et al. (2010) are the first to diagnose cross-cultural differences in the newsvendor problem. They show that the "pull-to-center" effect is more significant for Chinese decision makers than American decision makers.

2.2. Supply Chain Contracting and Coordination

In a typical supply chain, each firm aims to maximize its own profit, and this decentralized decision making reduces total supply chain profits (Spengler 1950). Supply chain contracts can be used to align the incentives of the firms with that of the supply chain, leading to supply chain "coordination". A coordinated supply chain achieves the profit level of a centralized firm. As summarized in Cachon (2003), researchers have studied different contract types to achieve coordination. Similar to our setting, these studies generally involve one manufacturer and one retailer, where the retailer faces the newsvendor problem. We compare the performances of the wholesale price contract, which is inefficient according to theory, with the buyback contract, which is a coordinating contract. Other coordinating contracts discussed in literature include quantity flexibility (Tsay 1999), revenue sharing (Cachon and Lariviere 2005), rebate (Taylor 2002) and quantity discount (Tomlin 2003).

Pasternack (1985) was the first to show that a buyback contract can coordinate a supply chain. Donohue (2000) extends this work by considering a second purchase opportunity. Taylor (2002) shows that a combination of buyback and target rebate contracts can coordinate the supply chain when demand is a function of the retailer's sales effort. Emmons and Gilbert (1998) and Kandel (1996) study coordination with buyback contracts when demand is price-sensitive.

Experimental work on supply chain contracting where the retailer faces a newsvendor problem is scarce. Katok and Wu (2009) study the buyback and revenue sharing contracts, focusing on their coordination capabilities. These authors, however, conduct experiments where only the manufacturer or the retailer is human; whereas the other firm is computerized. Hence, they ignore the strategic interaction between two human players. Our work is an extension of Keser and Paleologo (2004). These authors study a manufacturer-retailer supply chain under a wholesale price contract, and conduct experiments where both sides are human. They find that manufacturers charge lower wholesale prices than predicted, and the retailers understock (contrary to Schweitzer and Cachon's observation) relative to the newsvendor quantity. As a result, total profits are around the theoretical predicted values; yet, the profits are more equitably shared between the two firms. The authors find support for a decision heuristic where the retailers anchor on some price-quantity combination in the first period and adjust around this point based on the changes in the offered wholesale price. We extend Keser and Paleologo's work by comparing the wholesale price contract with the buyback contract and by comparing long-run and short-run relationships between the subjects. Some of our findings support theirs; however, there are also differences.

Marketing literature also studies supply chain coordination. In marketing models, the retailer faces a deterministic downward sloping demand function (Tirole 1998) rather than the newsvendor problem. The retailer does not face any inventory risk due to the deterministic nature of the problem. Rather than determining the stock quantity, the retailer determines the "sales price" to consumers, which in turn determines the sales and stock quantity according to the demand function. Supply chain inefficiency due to decentralized decision making is present, and is known as the "double marginalization problem" (Spengler 1950). The retailer sets a higher sales price than the supply chain optimum, leading to lower sales quantity, and lower total supply chain.

Within this setting, Ho and Zhang (2008) show that contrary to analytical models' predictions; the introduction of a fixed fee does not improve the supply chain's profit. In addition, the framing of the fixed fee makes a difference: A quantity discount results in higher chain profit than a two-part tariff. The authors develop a behavioral model to explain the outcome based on the two contracts' differences with respect to (1) framing (through loss aversion) (2) contract complexity (through bounded rationality). Lim and Ho (2007) find that increasing the number of blocks in a pricing contract from one to two increases channel profits, but not as much as predicted. Furthermore, contrary to theoretical prediction, increasing the number of blocks from two to three increases channel efficiency further. The authors explain this result by a Quantal-Response Equilibrium (QRE) model that accounts for retailers' sensitivity to counterfactual profits.

Özer et al. (2011) study the role of trust in forecast information sharing by using the wholesale price contract. They analyze whether and how cooperation can arise without complex contracts and reputation-building mechanisms by conducting experiments.

The information sharing and supply chain coordination literature assumes that supply chain members either absolutely trust each other and cooperate or do not trust each other at all. Contrary to this all-or-nothing view, Özer et al. find a continuum between these two extremes when people share information.

Supply chain contracting requires the study of relations between at least two independent decision makers (firms). This requires one to think about strategic/social factors in addition to individual decision biases we discussed in Section2.1. For example, rather than being purely self-interested, as assumed by standard economic theory, people may also care about "fairness" and the well being of the others. In an analytical study, Cui et al. (2007) show that a simple wholesale price contract can achieve coordination when firms are concerned about fairness. Pavlov and Katok (2009) develop a model to explain contract rejections and the more equitable sharing of profits between the firms where the manufacturer has incomplete information regarding the retailer's preference for fairness. Loch and Wu (2008) study the effect of social considerations in a wholesale price contracting setting where the manufacturer and the retailer interact repeatedly, similar to our long-run relationship experiments. These authors show that relationship and status seeking considerations can shift the equilibrium behavior of the subjects significantly. Haruvy et al. (2011) find that allowing negotiation between the subjects significantly increases the efficiency of coordinating contracts relative to the wholesale price contract. The manufacturers offer more efficient contracts and retailer rejections are almost eliminated when the firms can negotiate.

2.3. Bullwhip Effect

Here, we discuss the research on the bullwhip effect. Although we do not study the bullwhip effect, we provide a short literature summary on it, because it is one of the most studied areas in the behavioral operations management literature. Bullwhip effect is the phenomenon of increasing order variability in the supply chain as one moves from downstream firms (such as the retailer) to upstream firms (such as the raw material supplier). While consumer demand for specific products does not change much, inventory and back-order levels are often observed to fluctuate considerably across the supply chain. This variability is detrimental to firms' performance as it increases operational costs and reduces service levels. In an analytical study, Lee et al. (1997) identified the four common "operational" causes of the bullwhip effect as demand signal processing, order batching, rationing gaming and price variations. In addition to these operational causes, the bullwhip effect also has "behavioral causes".

The bullwhip effect can be studied by simulations of "Beer Distribution Game", a role-playing simulation of a simple production and distribution system developed by MIT in the 1960s (Simchi-Levi et al., 2008). Sterman (1989) was the first to use the beer game to test the existence of the bullwhip effect in an experimental setting. He explained the major behavioral causes of the bullwhip effect as "misperceptions of feedback" and "participants' tendency to underweight the supply line".

Croson and Donohue (2003) show that the bullwhip effect still exists when one removes all operational causes. Croson and Donohue (2005) show that access to downstream inventory information significantly reduces order fluctuation, with the most significant improvement at upstream levels. If upstream inventory information is accessible, however, no significant improvement is gained throughout the supply chain. On the contrary, Steckel et al. (2004) show that sharing point of sale information results in increasing costs, when the distribution of demand is non-stationary and unknown. Wu and Katok (2006) show that if supply chain partners are allowed to communicate and share their knowledge, supply chain performance improves significantly. Otherwise, individually improved knowledge does not increase the whole system's efficiency. Croson and Donohue (2006) find that underweighting of the supply line is present when customer demand is stationary and announced to all echelons.

CHAPTER 3

3. ANALYTICAL BACKGROUND

3.1. Buyback Contract Model

Consider a manufacturer who produces a product and a retailer who sells the product to consumers. At the beginning of the relation, the manufacturer determines the contract parameters wholesale price w, and buyback price b, and offers the contract to the retailer. Given the contract parameters, the retailer determines her stock quantity, Q. If the retailer's expected profit with this stock quantity is negative, the retailer rejects the contract. Else, the retailer orders this quantity from the manufacturer. This is the only opportunity to order for the retailer. The manufacturer produces Q units at a per unit cost of c, and delivers these units to the retailer. The retailer stocks this quantity before the selling season. Finally, random consumer demand D is realized during the selling season.

- If the realized consumer demand turns out to be lower than the retailer's stock quantity (i.e., if $D<Q$), some products are unsold at the retailer. As agreed in the contract, the manufacturer buys back these leftover units from the retailer by paying her b per unit.
- If the realized consumer demand turns out to be higher than the retailer's stock quantity (i.e., If $D>Q$), some demand will be unsatisfied. There is no extra penalty for unsatisfied demand to either firm; however, the firms lose the opportunity to make more profit.

The sequence of events can be summarized as follows:

1. The manufacturer offers a buyback contract (w, b).
2. If the retailer's expected profit level is non-negative, the retailer accepts the contract and determines her stock quantity Q.

3. The manufacturer produces Q units at a cost of c each, and ships these to the retailer.
4. Random consumer demand D realizes at the retailer.
5. The retailer sells the products to the customer at a cost of p per unit to satisfy the demand.
6. If there are leftover units at the retailer, the manufacturer buys back these by paying the retailer the buyback price b per unit. The manufacturer salvages these units and gains the salvage value v per unit.

The firms are risk neutral. Each aims to maximize its expected profit. To determine the manufacturer and the retailer's decisions, and to calculate the expected sales quantity and profit levels, one can solve this game backwards to find the subgame perfect equilibrium. First, one solves the retailer's problem below:

$$\underset{Q}{maximize}\ \pi_r^b = pE[\min(Q,D)] + bE[Q - \min(Q,D)] - wQ$$

$$= (p-b)E[\min(Q,D)] - (w-b)Q. \qquad (1)$$

Given the contract parameters w and b, the retailer faces the standard newsvendor problem (Nahmias 2009). The retailer's optimal stock quantity is found as:

$$Q^*(w,b) = F^{-1}\left(\frac{c_u}{c_u+c_o}\right) = F^{-1}\left(\frac{p-w}{p-b}\right). \qquad (2)$$

where $F^{-1}(.)$ is the inverse cumulative distribution function of demand D, c_u is the cost of underage, and c_o is the cost of overage. The term $\left(\frac{p-w}{p-b}\right)$ is the referred to as the "critical ratio".

In the case that the demand is uniformly distributed between D_{min} and D_{max}, retailer's optimal stock quantity is

$$Q^*(w,b) = \left(\frac{p-w}{p-b}\right) * (D_{max} - D_{min}) + D_{min}. \qquad (3)$$

The manufacturer anticipates the retailer's Q^* selection as a function of the contract parameters *(w,b)* that he offers. Substituting $Q^*(w,b)$, the manufacturer's problem becomes

$$\underset{w,\, b}{maximize}\ \pi_m^b = (w-c)Q^* - (b-v)E[Q^* - min(Q^*, D)]. \quad (4)$$

This function is not jointly concave in *w* and *b* (see Lariviere 1997). Hence, one cannot find a closed form solution for the manufacturer's optimal contract parameters. Instead, one can use a numeric procedure to determine the manufacturer's optimal contract parameters (w^*, b^*) through a grid search over possible *(w,b)* combinations. Using these contract parameters, one can then calculate the retailer's stock quantity, the expected sales quantity, and the expected profits of the two firms.

3.1.1 Supply-Chain Optimal Solution

The preceding analysis solves the problem from the manufacturer's point of view. One is also interested in the decision values that maximize the supply chain's total expected profit (i.e., the sum of manufacturer and retailer's expected profits). The supply chain's problem is formulated as

$$maximize\ \pi_{total}^{sc}(Q) = (p-v)E[\min(Q, D)] - (c-v)Q\ . \quad (5)$$

This is also a newsvendor problem. Note that the contract parameters *(w,b)* are irrelevant for the supply chain's problem because these decisions are between the supply chain firms. The stock quantity that maximizes the supply chain's expected profit is:

$$Q^{sc} = F^{-1}\left(\frac{c_u}{c_u + c_o}\right) = F^{-1}\left(\frac{p-c}{p-v}\right) \quad (6)$$

The supply chain's expected profit with stock quantity Q^{sc} is equal to

$$\pi_{total}^{sc}(Q^{sc}) = (p-v)E[\min(Q^{sc}, D)] - (c-v)Q^{sc}. \quad (7)$$

We observe that the supply chain expected profit is a function of the retailer's stock quantity decision Q. It is not affected directly by the manufacturer's contract term decisions (w,b). Hence, if the retailer chooses Q^{sc}, the supply chain achieves its theoretical maximum expected profit. In this case, the supply chain is said to be *coordinated*. The maximum profit level is known as the *integrated firm profit* (or, the centralized solution) because this is what a vertically-integrated firm would achieve.
In this setting, manufacturer's contract parameters (w, b) have two functions:

1) They affect the retailer's stock quantity Q choice. From equation (4), one can verify that any *(w, b)* pair that satisfies $b = \frac{p(w+v-c)- vw}{p-c}$ causes the retailer to choose Q^{sc} as her stock quantity.

2) They determine how the total supply chain profit is to be shared between the firms. Higher w values favor the manufacturer whereas higher b values favor the retailer.

Hence, if the manufacturer offers contract parameters (w,b) that satisfy $b = \frac{p(w+v-c)- vw}{p-c}$, the supply chain expected profit is maximized. However, the manufacturer's objective is to maximize his own expected profit, and he does not choose *(w,b)* that would theoretically result in Q^{sc} as the contract parameters. This causes the supply chain expected profit to be suboptimal, leading to supply chain "inefficiency". The ratio of the total supply chain profit under a given contract to the integrated firm profit level is referred to as the "efficiency" of the contract.

3.1.2 Our Experimental Setting and its Analytical Solution

We consider the following parameters:

- Unit production cost, $c = 50$
- Retail price, $p = 250$
- Salvage value, $v = 0$ (i.e., no salvage value)
- Demand, D, uniformly distributed between 40 and 230, and can take only integer values.

- The decision variables (w, b, Q) are expected to take only integer values.

These are the parameter values used by Keser and Paleologo (2004). Given these parameters, the manufacturer's wholesale price satisfies $w \geq c = 50$ and $w \leq p = 250$. For a chosen *w*, the buyback price satisfies $0 \leq b \leq w$.

3.1.2.1. Retailer's Problem

Given a contract (*w*,*b*), from Equation (3), the retailer's best response (i.e., optimal) stock quantity is

$$Q^*(w,b) = 190 * \left(\frac{250 - w}{250 - b}\right) + 40$$

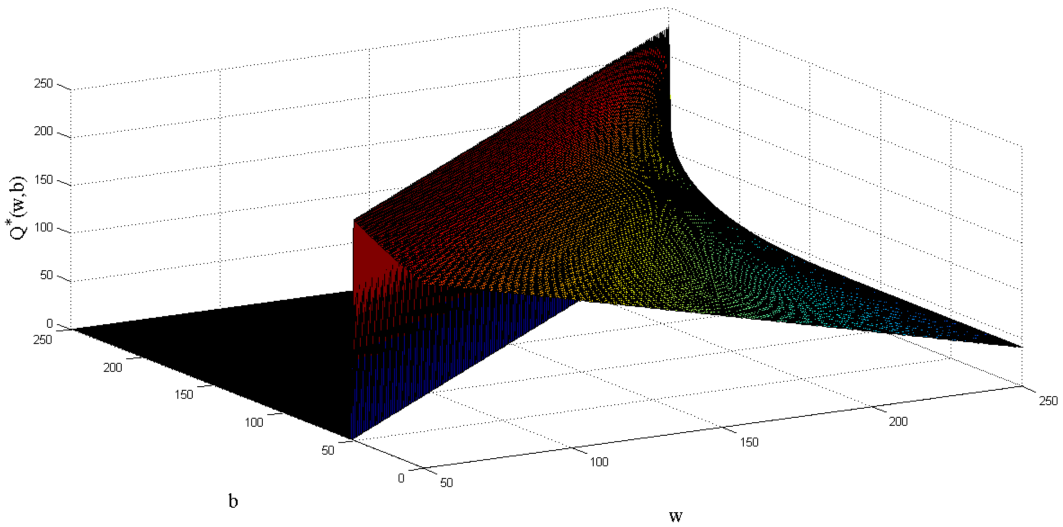


Figure 3.1.1 Theoretical Best Response for a Given Contract *(w,b)*

Figure 3.1.1 illustrates *Q*(w,b)*. We observe that the retailer's best response stock quantity increases with the buyback price and decreases with the wholesale price. The contract parameters *(w,b)* that satisfy $b = \frac{250(w-50)}{200}$ coordinate the supply chain and maximize the total supply chain profit. Such contracts cause the retailer to order the supply chain optimal stock quantity of $Q^{sc}=192$. From Figure 3.1.1, we observe that other *(w,b)* values cause the retailer to order and stock a lower quantity.

Given decisions (*w, b, Q*(w,b)*), one can calculate the retailer's profit for a given consumer demand, *D* realization as follows:

$$\begin{aligned}\pi_r^b(Q,D) &= pE[\min(Q,D)] + bE[Q - \min(Q,D)] - wQ \\ &= (p-b)E[\min(Q,D)] - (w-b)Q. \qquad (8)\end{aligned}$$

Recall that we assume each firm to act risk neutral, in which case its objective is to maximize its expected profit level. Retailer's *expected* profit is calculated over all possible demand realizations, which are integer values between 40 and 230. Because there are 191 possible integer values in this domain, each one is realized with a probability of 1/191.

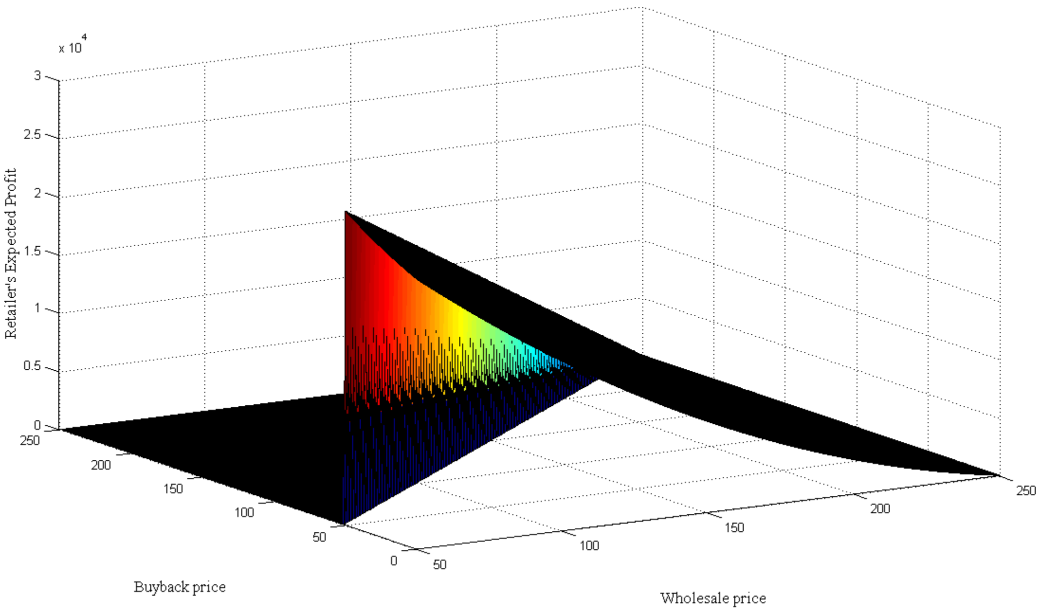


Figure 3.1.2 Retailer's Expected Profit

Figure 3.1.2 shows the retailer's expected profit as a function of contract parameters when she chooses her best response stock quantity *Q*(w, b)*. We observe that not surprisingly, the retailer's expected profit is maximized when the manufacturer sets $w = b = 50$. Because $w = b$, the retailer is under no risk, and hence, stocks the maximum possible demand quantity $Q = 230$. The profit margin $p\text{-}w$ is also at the maximum possible value. However, it is not likely that the manufacturer will set $w = b = 50$ because this means selling the product to the retailer at the unit production cost, and also buying back unsold quantities at full wholesale price. In fact, $w = b = 50$ yields a negative expected profit value of -4,750 for the manufacturer.

3.1.2.2 Manufacturer's Problem

The manufacturer anticipates the retailer's best response stock quantity Q*(w, b) choice for any contract (w,b) he may offer. Given the ($w,b,Q^*(w,b)$) values, the manufacturer can calculate his expected profit over the random consumer demand realization. This expected profit is shown in Figure 3.1.3 as a function of (w,b).

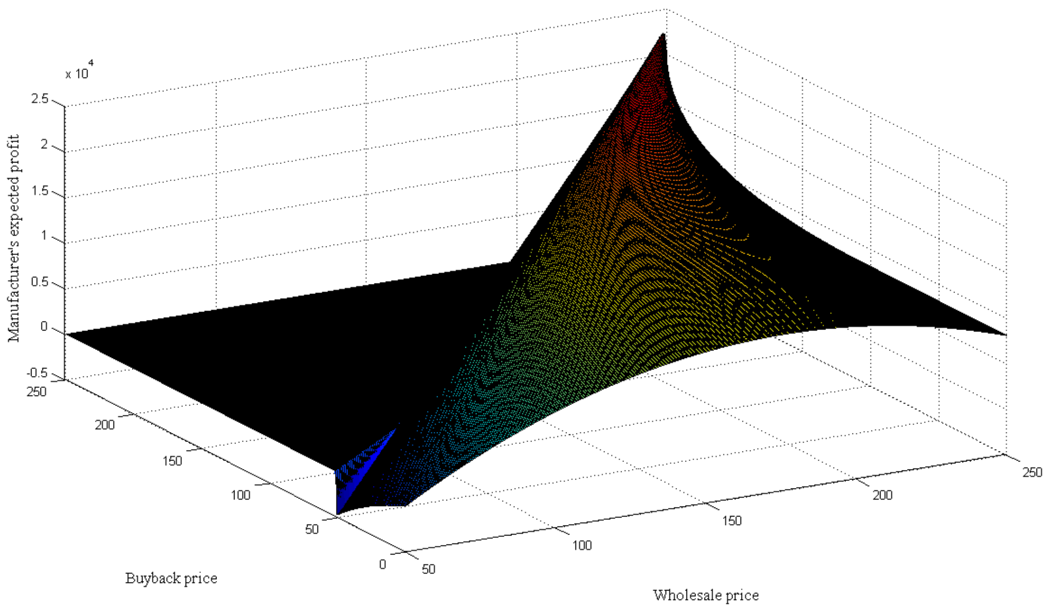


Figure 3.1.3 Manufacturer's Expected Profit

We observe that for a given b value, manufacturer's expected profit first increases with w, and then decreases. The direction of change depends on the retailer's best response quantity decision $Q^*(w,b)$. For example, if we fix $b = 80$, the manufacturer's expected profit is -700 for $w = b = 80$. For $80 \leq w \leq 183$, the manufacturer's expected profit increases. After $w = 183$, we observe a decrease in manufacturer's expected profit. As w increases, the manufacturer's profit margin per unit sold to retailer increases; however, the retailer stocks fewer units. Therefore, we cannot tell whether the manufacturer's expected profit increases or decreases in b for a given w value. The direction of change, again depends on the retailer's best response quantity decision $Q^*(w,b)$. For example, if one sets $w = 180$, manufacturer's expected profit is 12,116 for $b = 0$, increases with b until $b = 143$, and then decreases.

Through a grid search, we find the contract parameters that maximize the manufacturer's expected profit as $w^* = 247$ and $b^* = 246$. Given these parameters, the retailer sets a stock quantity of Q^*= 183. The resulting expected profits for the manufacturer, retailer and the total supply chain are 22,790, 333 and 23,123 respectively.

Note that the manufacturer's optimum w and b are quite close to their maximum levels of $p = 250$, and to each other. The manufacturer finds it optimal to sell the product at a high wholesale price, but at the same time, offer a generous buyback policy. With such a contract, the manufacturer is assuming most of the inventory risk in the supply chain. The retailer's critical ratio is 0.75, leading to a high stock quantity. This outcome is due to the relatively low unit production cost ($c = 50$) with respect to the high sales price ($p = 250$).

3.1.2.3 Supply Chain Optimal Solution

Figure 3.1.4 illustrates supply chain expected profit as a function of the contract parameters.

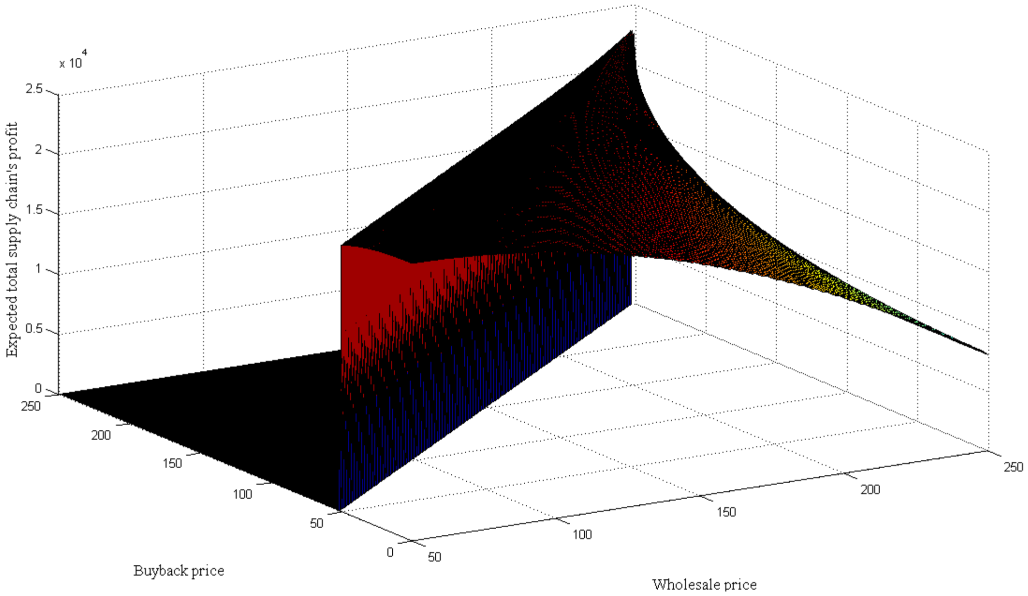


Figure 3.1.4 Total Supply Chain Expected Profit for every *(w,b)* pair

We observe that the highest expected supply chain profit occurs for (w, b) values that satisfy $b^* = \frac{250(w-50)}{250-50} = \frac{5w}{4} - 62.5$. This is an expected outcome. These (w, b) pairs satisfy the coordination condition and coordinate the supply chain. In other words, given these (w,b) couples, the retailer's critical ratio is equal to the supply chain's critical ratio of 0.80. As a result, the retailer chooses $Q^{sc} = 192$ as the stock quantity, leading to a total supply chain expected profit of 23,200.

Recall that in the manufacturer's optimal solution, we found the retailer to set Q^* =183, leading to a supply chain expected profit of 23,123. The efficiency of the contract in the manufacturer's optimal solution is then equal to $23{,}123 / 23{,}200 = 99.67\%$, which is quite high. That is, the solution that maximizes the manufacturer's profit is also a good one from the supply chain point of view. Note however that this solution leaves only a small expected profit of 333 to the retailer.

3.2. Wholesale Price Contract Model

Next, we provide the solution of the same model under a wholesale price contract. Note that the wholesale price contract model is a special case of the buyback contract model. The sequence of events is the same except that the manufacturer does not buy back unsold inventory from the retailer. To carry out the analysis, we simply substitute $b = 0$ in the buyback contract analysis. The retailer's problem becomes,

$$\underset{Q}{maximize}\ \pi_r^w = pE[\min(Q, D)] - wQ. \tag{9}$$

The quadratic and concave objective function implies a unique optimum

$$Q^*(w) = F^{-1}\left(\frac{p-c}{p}\right). \tag{10}$$

Because demand is uniformly distributed in our experimental setting, the unique optimum, as validated also by our simulation, is

$$Q^*(w) = \begin{cases} D_{max} - \frac{w(D_{max}-D_{min})}{p} & if\ w < p \\ 0 & if\ w \geq p \end{cases}. \tag{11}$$

The manufacturer anticipates the retailer's Q^* selection as a function of the contract parameter *w* he offers. Substituting *Q*(w)*, the manufacturer's problem becomes

$$maximize\ \pi_m^w = (w - c)\ \mathrm{Q}^*. \tag{12}$$

The objective function of the manufacturer is quadratic and concave in the interval $[c, p]$ and is equal to zero if *w*>*p*. The optimal wholesale price is found as

$$w^* = \min\left\{p, \frac{c}{2} + \frac{p}{2}\frac{D_{max}}{D_{max}-D_{min}}\right\} \tag{13}$$

In the subgame perfect solution of the game, the manufacturer offers the wholesale price, w^*, and the retailer's stock quantity is

$$Q^*(w^*) = \frac{D_{max}}{2} - c\left(\frac{D_{max} - D_{min}}{2p}\right). \quad (14)$$

Alternatively, one may use a numeric procedure to determine the manufacturer's optimal wholesale price, w^*, through a grid search over possible w values. Using this wholesale price, one can then calculate the retailer's stock quantity, expected sales quantity, and the expected profits of the two firms.

3.2.1 Our Experimental Setting and its Analytical Solution

Based on numerical calculations, we find the wholesale price that maximizes the manufacturer's expected profit as $w^* = 176$. Given this w^*, the retailer sets a stock quantity of $Q^* = 96$. The resulting expected profits for the manufacturer, retailer and the supply chain are 12,126, 5,011 and 17,137 respectively.

3.2.1.1 Supply Chain Optimal Solution

The wholesale price that maximizes the total supply chain profit is $w^{sc} = c = 50$. Given this wholesale price, the retailer would choose $Q^{sc} = 192$ as the stock quantity. Total supply chain expected profit would be 23,200. Note that this is equal to the optimal total supply chain profit (i.e., the integrated firm profit) we discussed in Section 3.1.2.3. The integrated firm profit is a benchmark independent of the contract used between the firms. The efficiency of a particular contract is calculated as the total supply chain profit under that contract to the integrated firm profit.

While $w^{sc} = c = 50$ maximizes the total supply chain profit, it is not likely that the manufacturer will set this wholesale price. Because this means selling the product to the retailer at the unit production cost, yielding no profit to the manufacturer. The manufacturer is predicted to set his own optimal $w^*=176$, leading to a total supply chain profit of 17,137. The efficiency of this contract is $17{,}137 \,/\, 23{,}200 = 74\%$.

3.3. Comparison of the Analytical Solutions Under Two Contracts

Table 3.3.1 compares the manufacturer's optimal solution under the two contracts.

Table 3.3.1 Comparison of Manufacturer's Optimal Solution under Two Contracts

Type of Contract	Total Profit	Contract Efficiency	Mfg. Profit	Retailer Profit	w	b	Q
Buyback	23,123	99.67%	22,790	333	247	246	183
Wholesale Price	17,137	74.00%	12,126	5,011	176	--	96

We observe that the manufacturer's optimal solution under the buyback contract dominates the one under wholesale price contract in parameters of total profits. This is primarily due to differences between the retailer's stock quantities. In fact, the efficiency under the buyback contract is close to 100%. This sounds like good news from the supply chain point of view. However, the profit distribution under the buyback contract is quite disturbing. The retailer's share of the profit is negligible with almost all profit going to the manufacturer. The wholesale price contract, on the other hand, while inefficient, offers the retailer a decent profit level.

Note that this is only a theoretical comparison which assumes that (1) the retailer will accept any contract that provides her nonzero expected profit; (2) the retailer will determine her stock quantity according to the newsvendor formula. As we will discuss, both of these assumptions are questionable when real human beings make decisions.

CHAPTER 4

4. EXPERIMENTAL DESIGN AND PROCEDURE

In this chapter we present our experimental design and procedure.

4.1. Experimental Design

We used the following parameter setting in all experiments:

- Unit production cost, $c = 50$
- Retail price, $p = 250$
- Salvage value, $v = 0$ (i.e., no salvage value)
- Demand, D, uniformly distributed between 40 and 230, and can take only integer values.
- The decision variables (w, b, Q) can only take integer values.
- Number of participants is denoted by n.

As illustrated in Table 4.1.1, we use two levels of experimental manipulations:

- Contract type manipulation
  - Buyback contract: The manufacturer offers a buyback contract (w,b)
  - Wholesale price contract: The manufacturer offers a wholesale price contract (w)

- Relationship length manipulation:
  - Long run: The same manufacturer-retailer pair interacts in all 30 periods.
  - Short run: The manufacturer-retailer pairs are re-assigned randomly in each period.

Table 4.1.1 Experimental Design and Number of Subjects

		Contract Type	
		Buyback	**Wholesale price**
Relationship Length	**Long run**	Experiment b1a, n=12 Experiment b1b, n=16	Experiment w1a, n=16 Experiment w1b, n=16 Experiment w1c, n=16
	Short run	Experiment b2a, n=12 Experiment b2b, n=16	Experiment w2a, n=16 Experiment w2b, n=16 Experiment w2c, n=16

4.2. Experimental Procedure

Our experiments are computer-based and were conducted at the CAFE (Center for Applied Finance Education) computer laboratory of Sabancı University, Faculty of Management. We coded[1] and implemented the experimental model using HP MUMS Software.

Subjects are selected from Sabancı University MS 401 course Spring semester 2010/2011 students. These students had already studied the basic newsvendor problem. To provide incentive, we converted the subjects' total profit at the end of the experimental session into a bonus grade for the course MS 401. The bonus ranged between 1% and 2.5%, and it is applied to the final grade of the subject in that course. We distributed instructions to the subjects before they arrive at the laboratory. Sample

[1] Appendix A provides the main script code that is used to define the number of subjects, and to call other functional scripts, as an example. Appendix B illustrates another important part of the code where the parameters, stages and the allocation strategy of subjects to the roles are defined.

instructions are provided in Appendix C. At the beginning of each session, we explained the experiment once again to ensure that the instructions are clearly understood, and we answered any remaining questions. Before starting the actual experiment, we let the subjects play three pilot (training) periods. During the actual experiments, we did not allow the subjects to communicate with each other. Each experimental session took around two hours.

Each experimental session contained one experiment (treatment) composed of 30 independent periods (rounds). Throughout a given experiment, a particular subject played the role of either manufacturer or retailer. The role was randomly assigned at the beginning of the experiment and remained unchanged in all of the 30 periods. We did not conduct any experiment where a particular subject may play different roles in different periods. This is consistent with the Keser and Paleologo (2004).

We use the term "game" to denote the interaction in a manufacturer-retailer pair in a period. The sequence of events in the game reflects the three stage interaction in the analytical model. At stage I of the game, the manufacturer sets the contract parameters wholesale price and buyback price (in buyback contract experiments). At stage II, these contract parameters are displayed on the retailer's screen and the retailer determines her stock quantity. At stage III, random consumer demand is realized. The results of the game are then reported to the subjects. Each subject is given around 30 seconds to make his decision.

Appendices D and E provide sample screenshots of the manufacturer and the retailer's screens respectively in the buyback contract experiments. The large table in the middle of the screen is the "decision support tool". By using this tool, the subjects could run what-if analysis before submitting their decisions. A retailer subject can enter a stock quantity to this tool and obtain the outcome for eight different realizations of the stochastic consumer demand (For $D = 40, 70, 100, 130, 160, 190, 220, 230$). The manufacturer also has a decision support tool. However, he needs to enter contract parameters (w, b), as well as a value for the retailer's stock quantity decision to the tool. More detailed explanation about the decision support tool can be found in Appendix C where we provide the instructions.

Subjects enter their decisions into the cells at the bottom of the screens. At the end of each period, a results screen (as seen in Appendix F) provides the subjects with the results of their game. The game results include the consumer demand realization; the decisions of both firms, number of units sold, and number of units unsold, demand unsatisfied, the period profit and cumulative profit of both firms. These results are provided for all periods up to and including the last period.

After each experiment, we conducted a post-experiment survey where we asked the subjects how they made their decisions, whether they were motivated by the bonus grade and their suggestions. These surveys indicated that the subjects were highly motivated for their decisions, and they gave us clues about their decision heuristics.

4.3. Experimental Data Analysis

Before presenting our result in Chapter 5, here we discuss how we analyzed experimental data. The two firms make a number of decisions in the model, and at the last stage, random demand is realized. We repeat the decision structure of the buyback contract model below:

1. The manufacturer determines the contract parameters (w,b). In theory, the manufacturer makes this decision by evaluating all possible contract parameter combinations, and choosing the one that gives him the highest expected profit. The chosen contract parameters determine

    - The critical ratio: This determines the newsvendor quantity.
    - Retailer's expected profit: This determines the "attractiveness" of the contract from the retailer's point of view. Lower wholesale price values and higher buyback price values result in more attractive contracts.
    - Expected profit shares of the manufacturer and retailer.

2. The retailer determines whether to accept or reject the contract. In theory, the retailer accepts any contract that provides her a non-negative expected profit.

3. If the contract is accepted, the retailer determines the stock quantity *Q*. In theory, the retailer determines the quantity through the newsvendor model as $Q^* = F^{-1}(\textit{critical ratio})$.
4. Finally, random demand *D* is realized.

Given this sequence, we compare the experimental data with two benchmarks:

1) Manufacturer's optimal outcome: The subgame-perfect equilibrium of the model corresponds to the manufacturer's optimal outcome (in each period). This is because the manufacturer is the first-mover in the game. In this outcome, the manufacturer offers the contract ($w^*=247$, $b^*=246$), and the retailer stocks the corresponding newsvendor quantity $Q^*(w^*, b^*) = 183$. Manufacturer's expected profit is 22,790 and retailer's expected profit is 333. This is what the theory predicts as the outcome of the overall interaction between the two firms in a given period.

2) Newsvendor prediction (predicted outcome): In experiments, manufacturer subjects do not necessarily offer their optimal contract (w^*, b^*). We define the "predicted outcome" as the expected outcome of the interaction given any contract (w, b), assuming that the retailer chooses the newsvendor stock quantity $Q^*(w, b)$. The difference between the "predicted outcome" and real experiment data is due to the retailer's deviation from the newsvendor model, and due to the realization of random demand.

4.3.1 The Unit of Analysis

Each experiment (treatment) consists of 30 periods, and in each period we have 6 to 8 manufacturer-retailer pairs making decisions (each corresponding to a "game"). The main unit of analysis we use is the period averages across manufacturer-retailer pairs. Hence, each experiment yields 30 data points. For some experiments, we also report analyses on subject-level data.

4.3.2 Contract Rejections

If the retailer rejects the contract through setting $Q=0$, both firms obtain zero profit. Consistent with the literature, we exclude the games with rejected contracts from the main analysis. We provide information on rejected contracts separately. Appendix G provides the summary results with and without rejected contracts. Note that the number of rejected contracts is not large in our experiments, and rejections do not affect our major results. Overall, only 1.8% of the proposed contacts were rejected. The highest percentage of rejected contracts in an experiment was 4.5% (in Experiment w2c).

4.3.3 What Do We Measure?

Primarily, we keep track of the subjects decisions' over periods. These are the contract parameters (w,b), and the stock quantity Q. Given these decisions and the realization of the random demand, D, we also calculate profit-related measures. These include retailer's profit, manufacturer's profit, total profit, contract efficiency (Total profit / integrated firm profit level) and profit shares of firms. In addition, we keep track of the retailer's predicted newsvendor profit corresponding to a given contract (w,b).

4.3.4 What Are We Interested In?

We are primarily interested in (1) Observing and comparing the experimental performances of the buyback and wholesale price contracts (2) Understanding the effect of the relationship length. In addition to these, we also aim to uncover if and how the subjects' decisions evolve over time. In particular, we expect to observe some "learning by doing" over time because the subjects are provided with results at the end of each period. Finally, we would like to understand the "decision heuristics" that the subjects might be using in making their decisions.

4.3.5 Statistical Tests

We have no prior assumptions on the distributions of the assessed variables; therefore we used non-parametric statistical tests (Siegel, 1956) such as the Wilcoxon Signed-Rank test and the Wilcoxon Rank-Sum test (the Mann-Whitney U test) to test statistical significance.

CHAPTER 5

5. RESULTS

In this chapter, we first make an overall comparison across all experiments to understand the effects of the relationship length and the contract type. The goal is to provide big-picture results. Then, we present a detailed analysis on our experiments.

5.1. Overall Comparison Results

Here, we compare experimental results to understand the effects of relationship length and the contract type. The unit of analysis is the mean value in a period across all games (i.e., manufacturer-retailer pairs) in a given experiment. Hence, each experiment yields 30 data points, corresponding to 30 periods. To obtain strong results, we pooled the data of similar experiments together. For example, by pooling the data of Experiments b1a and b1b, we obtain 60 data points for b1 experiments. Table 5.1.1. summarizes the comparison.

Table 5.1.1 Overall Comparisons

		Contract Type	
		Buyback	**Wholesale Price**
Relationship Length	**Long Run**	b1 experiments 60 data points	w1 experiments 90 data points
	Short Run	b2 experiments 60 data points	w2 experiments 90 data points

In what follows, we first discuss the results of the buyback contract experiments. We compare the data with the manufacturer's optimal solution. Then, we compare the long and short run relationship results. Next, we discuss the results of the wholesale price experiments. Finally, we compare the buyback and wholesale price contract experiment results.

5.1.1. Buyback Contract Experiments

Table 5.1.2 provides the descriptive statistics for the buyback contract experiments. Bold p-values represent the results with significant median differences according to Wilcoxon Rank Sum Test.

Table 5.1.2 Comparison of Buyback Experiments

Buyback Contract	Mfg. Optimal		Buyback All (m+n=120)	p-value	Long Run (b1, m=60)	Short Run (b2, n=60)	p-value
Total Profit	23,123	Mean	19,010		18,697	19,323	
		Median	18,375	**0.000**	18,000	18,700	**0.000**
		Stdev	8,724		9,278	9,228	
Mfg. Profit	22,790	Mean	13,297		13,714	12,879	
		Median	12,725	**0.000**	12,513	12,490	**0.004**
		Stdev	5,135		6,232	4,989	
Retailer Profit	333	Mean	5,714		4,983	6,444	
		Median	5,743	**0.000**	4,365	7,000	**0.004**
		Stdev	6,494		6,211	6,603	
Retailer Predicted Profit	333	Mean	6,143		5,414	6,872	
		Median	6,201	**0.000**	4,892	7,087	**0.000**
		Stdev	2,924		3,271	2,397	
w	247	Mean	175		182	167	
		Median	175	**0.000**	190	167	**0.000**
		Stdev	26		30	22	
b	246	Mean	76		88	64	
		Median	55	**0.000**	65	47	**0.000**
		Stdev	52		52	49	
Q	183	Mean	127		125	129	
		Median	125	**0.000**	120	125	0.164
		Stdev	44		50	48	

Recall that the theoretical predicted outcome of the interaction is the manufacturer's optimal solution that we outlined in Chapter 3. First, we would like to know if experimental data is in line with this solution.

HYPOTHESIS-1 (THEORETICAL BENCHMARK, BUYBACK CONTRACT): The outcome of the interaction will be as described by the manufacturer's optimal solution. Specifically, w=247, b=246, Q=183 with a total profit of 23,123, where the manufacturer gains 22,790 and the retailer gains 333.

Experiment data strongly rejects this hypothesis. Instead of offering the optimal contract which provides only a tiny profit to the retailers, the manufacturers offered much more acceptable contracts that yield a decent profit level to the retailers. These contracts had lower wholesale price, and much lower buyback prices than the manufacturer's optimal solution. Retailer's stock quantities are much lower than those in the optimal solution. However, they are higher than the predicted levels (i.e, the best response levels) given contract. Total profit level, which depends on the retailer's stock quantity, is well below the one in the optimal solution. Yet, this profit is more equitably shared between the manufacturer and the retailer.

Next, we study the effects of relationship length by comparing the long-run (i.e., fixed partner) experiments with short-run (i.e., variable partner) experiments. We expect higher profit levels for both firms in a long-run relationship. In these experiments, each partner knows that he will be playing with the other partner in all of the 30 periods. The partners are likely to get to know each other and learn their strategies during the experiment over time according to the decisions of both parties.[2]. The manufacturer should be offering more attractive contracts, and the retailer should be stocking higher quantities in response. In short-run relationship experiments, both partners know that the relationship is one shot[3]. Hence, we expect the partners to act more myopically, leading to opportunistic behavior.

HYPOTHESIS-2 (LENGTH OF RELATIONSHIP, BUYBACK CONTRACT): Profit levels (retailer, manufacturer, total) will be higher under a long-run relationship than those under a short-run relationship.

[2] Note that players are not allowed to communicate during experiments.
[3] Even though they may be re-matched in a future period, they will not know about it.

Experimental data rejects this hypothesis. We observe the retailer's profit and total profit to be significantly higher in short-run relationships; whereas the manufacturer's profit is significantly lower. We observe the manufacturers to offer more attractive contracts in terms of retailer's predicted profit in the short-run relationships, probably due to the fear of rejection by the "unknown" retailer. This leads to higher stock quantities, which is preferable from the supply chain point of view. Another explanation is that the subjects engaged in destructive "strategic gaming" in the long-run relationships. To obtain higher profits in the long run, they may be making aggressive decisions (manufacturers offering unattractive contracts, and/or retailers frequently rejecting contracts) in the initial periods to "signal" that they are tough players.

5.1.2. Wholesale Price Contract Experiments

Table 5.1.3 provides descriptive statistics for the wholesale price contract experiments.

Table 5.1.3 Comparison of Wholesale Price Contract Experiments

Wholesale Price Contract	Mfg. Optimal		Wholesale All (m+n=180)	p-value	Long Run (w1, m=90)	Short Run (w2, n=90)	p-value
Total Profit	17,137	Mean	19,120		18,456	19,794	
		Median	18,250	**0.000**	17,250	20,000	**0.002**
		Stdev	8,895		8,857	8,617	
Mfg Profit	12,126	Mean	12,350		12,134	12,565	
		Median	12,000	0.142	11,700	12,254	**0.000**
		Stdev	4,589		5,045	3,790	
Retailer Profit	5,011	Mean	6,775		6,322	7,229	
		Median	7,500	**0.001**	7,150	8,000	**0.016**
		Stdev	8,080		7,691	8,455	
Retailer Predicted Profit	5,011	Mean	7,517		7,495	7,868	
		Median	7,770	**0.000**	7,470	7,770	0.212
		Stdev	2,836		2,606	3,048	
w	176	Mean	152		154	151	
		Median	150	**0.001**	150	150	**0.001**
		Stdev	25		24	26	
Q	96	Mean	125		119	130	
		Median	150	**0.000**	115	125	**0.000**
		Stdev	45		47	39	

First, we would like to know if experimental data is in line with the theoretical predicted outcome, the manufacturer's optimal solution that we studied in Chapter 3.

HYPOTHESIS-3 (THEORETICAL BENCHMARK, WSP CONTRACT): The outcome of the interaction will be as described by the manufacturer's optimal solution. Specifically, w=176, Q=96 with a total profit of 17,137 where the manufacturer gains 12,126 and the retailer gains 5,011.

Experiment data strongly rejects this hypothesis. The manufacturer's profit, the retailer's profit, and total profit are significantly higher than those in the manufacturer's optimal solution. This counterintuitive outcome is driven by the manufacturer's offering of more attractive contracts (i.e., lower w). The retailers, in turn, stocked even more than the theoretical best response prediction.

The overstocking reaction of the retailers is also crucial within the scope of Schweitzer and Cachon (2000)'s pull-to-center effect observation. In their experiments, retailers overstocked for products that have high (higher than 50%) profit margin, whereas they understocked products that have low (lower than 50%) profit margin. This observation, however, conflicts with Keser and Paleologo (2004). Our experimental results can be seen in Chapter 6.

Next, we study the effects of the relationship length by comparing the long-run and short-run relationship experiments. Again, we expect the long-run relationships to perform better.

HYPOTHESIS-4 (LENGTH OF RELATIONSHIP, WSP CONTRACT): Profit levels (retailer, manufacturer, total) will be higher under a long-run relationship than those under a short run relationship.

Similar to Hypothesis 2, experimental data rejects this hypothesis as well. We observe the retailer's profit and total profit to be significantly higher in short-run relationships; whereas the manufacturer's profit is lower. The manufacturers offer more (however, not significantly more) attractive contracts in terms of retailer's predicted profit in the short run relationships, probably due to the fear of rejection by the "unknown" retailer. This leads to higher stock quantities, which is preferable from the supply chain point of view.

5.1.3. Comparison of the Buyback and Wholesale Price Experiments

Here we compare the performances of the two contract types. Based on supply chain contracting literature, we expect the buyback contract to achieve higher total supply chain profit than the wholesale price contract. Also, we expect the manufacturer's profit to be higher under the buyback contract. This is because the manufacturer is the one who offers contract parameters, and the wholesale contract is only a special case of the buyback contract with $b = 0$.

HYPOTHESIS-5 (CONTRACT COMPARISON): (5a) Total profit and (5b) the manufacturer's profit will be higher under the buyback contract than under the wholesale price contract.

Table 5.1.4 provides descriptive statistics for the comparison.

Table 5.1.4 Comparison of the Buyback Experiments with the Wholesale Price Contract Experiments

	Mfg.'s Optimal Solution		**Experiment Data**			
	Buyback Contract	WSP Contract		Buyback All (m+n=120)	Wholesale All (m+n=180)	p-value
Total Profit	23,123	17,137	Mean	19,010	19,125	0.346
			Median	18,375	18,250	
			Stdev	8,724	8,895	
Efficiency	99.70%	73.70%	Mean	81.9%	82.40%	0.634
			Median	77.6%	78.70%	
			Stdev	39.9%	38.30%	
Mfg Profit	22,790	12,126	Mean	13,297	12,350	**0.000**
			Median	12,725	12,000	
			Stdev	5,135	4,589	
Retailer Profit	333	5,011	Mean	5,714	6,775	**0.002**
			Median	5,743	7,500	
			Stdev	6,494	8,080	
Retailer Predicted Profit	333	5,011	Mean	6,143	7,517	**0.000**
			Median	6,201	7,770	
			Stdev	2,924	2,836	
Q	183	96	Mean	127	125	0.091
			Median	125	150	
			Stdev	44	45	

Experiment data rejects Hyphothesis-5a. The total profit under the buyback contract is not significantly higher than that under the wholesale price contract. This finding is interesting because the buyback contract holds the potential to "coordinate" the supply chain, whereas the wholesale price contract is known to be inefficient in theory. Recall that in our parameter setting, the buyback contract is coordinating when $Q^{sc}=192$, with a total supply chain profit of 23,200. The manufacturer's optimal solution with the buyback contract yields a total profit of 23,123, which is quite close to the total profit under coordination. If the manufacturer offered his optimal buyback contract to a rational retailer (i.e., a computerized retailer), the outcome would be quite efficient. However, human retailers would probably reject a contract that offers an expected profit of only 333. Hence, it is understandable that this contract is not offered. However, the manufacturer is not offering buyback contracts that have high contract efficiency at all. The average efficiency of the buyback contracts in experiments is around 82%, with a total profit of 19,010.

In theory, the wholesale price contract cannot coordinate the supply chain unless $w = c = 50$, which is not likely to be offered by the manufacturers. In fact, the average efficiency of the wholesale price contracts in our experiments is 82%, (80% in long-run relationships and 84% in short-run relationships). It is surprising that the average efficiency of the buyback and wholesale price contracts turned out to be close to each other.

While Hypothesis 5a is rejected, data supports Hypothesis 5b. We observe the buyback contract to increase the manufacturer's profit, while reducing the retailer's. Actually, the buyback contract, with its two "levers" makes it easier for the manufacturers to capture profits from the retailers. This observation, combined with the discussion around Hypothesis 5a indicates that rather than improving supply chain efficiency, the buyback contract may serve as a tool to transfer retailer's profit to manufacturer. This finding questions the intentions in real-life usage of the buyback contract.

Our results contradict existing results in experimental literature. In the experiments of the current literature, however, only one partner is human, and the other is computerized. Hence, the difference in observations is probably due to the existence of "strategic interaction" between two human players. Our results imply that the findings of one-sided experiments should be used with caution when there is strategic interaction between parties. Recently, other researchers have also reported experimental studies which find the wholesale price to perform better than theoretical prediction.

Finally, as Table 5.1.5 illustrates, the comparisons we made between the two contract types are robust if one analyzes the long-run and short-run relationship experiments separately.

Table 5.1.5 Comparison of Long-Run Relationship with Short-Run Relationship

		Long-Run Relationship			**Short-Run Relationship**		
		Buyback (b1, m=60)	Wholesale (w1, n=90)	p-value	Buyback (b2, m=60)	Wholesale (w2, n=90)	p-value
Total Profit	Mean	18,697	18,456		19,323	19,794	
	Median	18,000	17,250	**0.000**	18,700	20,000	**0.000**
	Stdev	9,278	8,857		9,228	8,617	
Efficiency	Mean	80.60%	79.60%		83.30%	85.30%	
	Median	77.60%	74.40%	0.511	80.60%	86.20%	0.222
	Stdev	40.00%	38.20%		39.80%	38.10%	
Mfg. Profit	Mean	13,714	12,134		12,879	12,565	
	Median	12,513	11,700	**0.000**	12,490	12,254	0.339
	Stdev	6,232	5,045		4,989	3,790	
Retailer Profit	Mean	4,983	6,322		6,444	7,219	
	Median	4,365	7,150	**0.002**	7,000	8,000	0.134
	Stdev	6,211	7,691		6,603	8,455	
Retailer Predicted Profit	Mean	5,414	7,495		6,872	7,868	
	Median	4,892	7,470	**0.000**	7,087	7,770	**0.000**
	Stdev	3,271	2,606		2,397	3,048	
Q	Mean	125	119		129	130	
	Median	120	115	**0.003**	125	125	0.595
	Stdev	50	47		48	39	

5.2. Experiment Results

5.2.1 Experiment b1a

Experiment b1a has six manufacturers and six retailers. Contract rejection is observed in three games.

5.2.1.1 Retailer's Stock Quantity Decision and Firms Profits

Here, we discuss the retailer's stock quantity decision and the firms' profits. We compare experimental data with theoretical prediction (based on retailer's newsvendor quantity for the given contract parameters) in each game.

Figures 5.2.1(a)-(c) present the mean stock quantity and the firms' profits across six games over 30 periods. Table 5.2.1 summarizes the comparison.

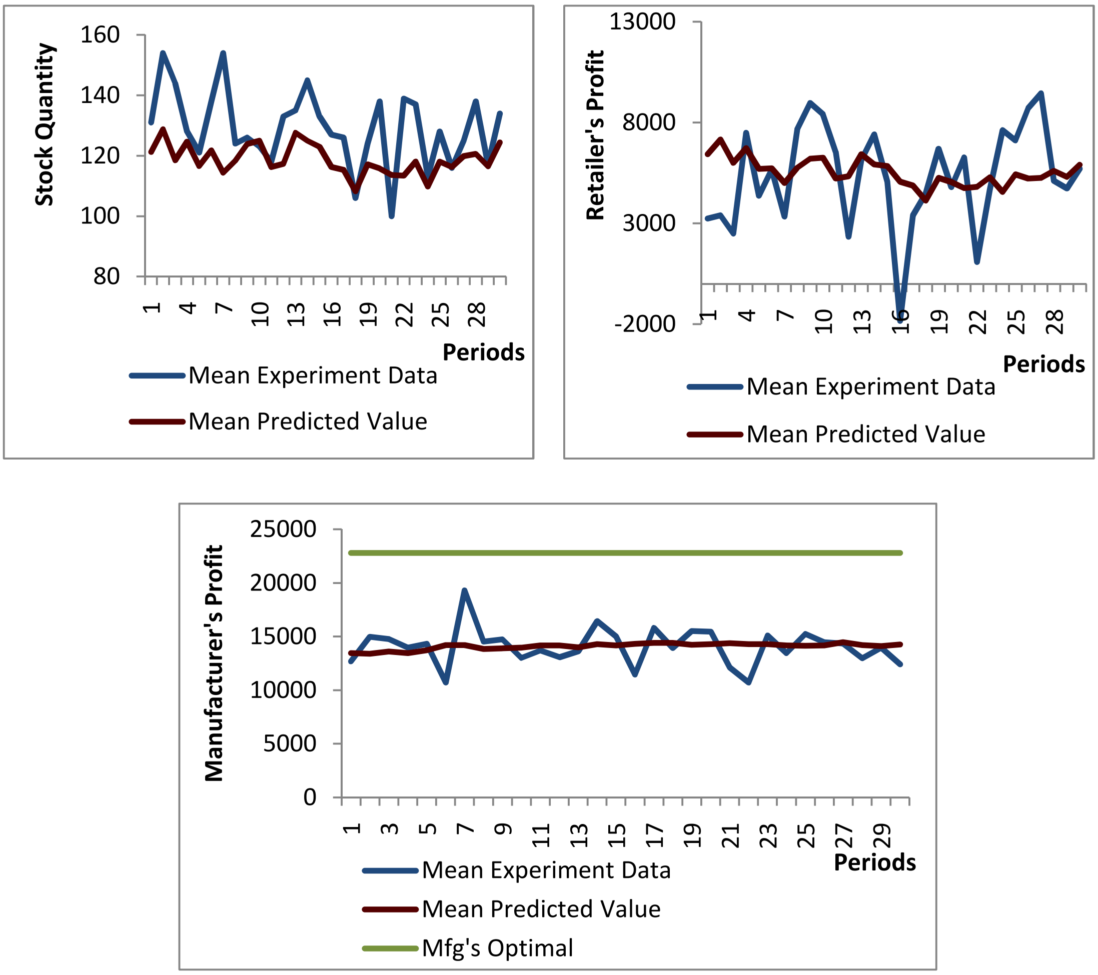


Figure 5.2.1 (a)-(c) Stock Quantity and Firms Profits in Experiment b1a

Table 5.2.1 Stock Quantities and Firms Profits in Experiment b1a

	Stock Quantity			**Retailer's Profit**			**Manufacturer's Profit**		
	Data	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**
Mean	129	*122*		5,350	*5,537*		14,066	*14,097*	
Median	128	*118*	**0.000**	5,388	*5,381*	0.766	14,155	*14,182*	0.586
St.dev.	12	*5*		2,523	*673*		1,741	*300*	

On average, we observe the retailers to overstock relative to their best response prediction as also seen in Figure 5.2.2. However, this over-stocking does not affect the retailers' or the manufacturers' profit significantly.

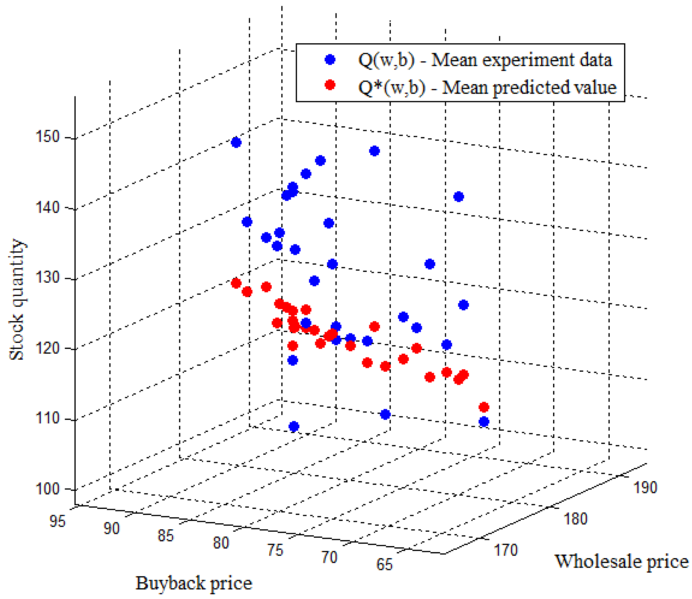


Figure 5.2.2 Comparison of *Q(w,b)* and *Q*(w,b)* in Experiment b1a

Next, we study the subject-level results to gain a more detailed understanding. Table 5.2.2(a)-(c) presents the results by manufacturer-retailer pairs. We observe five out of six retailers to overstock, two of them significantly.

Table 5.2.2 (a)-(c) Stock Quantity Decisions and Firms Profits in Experiment b1a

Stock Quantity	**Ret-1**	**Ret-2**	**Ret-3**	**Ret-4**	**Ret-5**	**Ret-6**	**Avr.**
Mean Data	86	134	160	119	127	142	129
Median Data	85	135	165	105	133	143	
Predicted Q*(w,b)	*106*	*130*	*164*	*84*	*109*	*137*	*122*
p-value	**0.000**	0.323	0.266	**0.000**	**0.001**	0.387	

Retailers Profit	**Ret-1**	**Ret-2**	**Ret-3**	**Ret-4**	**Ret-5**	**Ret-6**	**Avr.**
Mean Data	3,768	4,655	12,349	2,532	4,690	3,593	5,350
Median Data	3,600	4,500	12,656	4,200	8,625	3,910	
Stdev	4,002	3,929	8,554	6,283	7,198	3,054	
Pred. Prof.	*5,030*	*4,971*	*13,023*	*3,079*	*5,776*	*3,599*	*5,537*
p-value	0.144	0.829	0.719	0.163	0.837	0.600	

Mfg. Profit	**Mfg-1**	**Mfg-2**	**Mfg-3**	**Mfg-4**	**Mfg-5**	**Mfg-6**	**Avr.**
Mean Data	10,508	15,869	8,964	17,244	15,094	16,532	14,066
Median Data	10,000	16,730	9,283	16,600	15,273	16,950	
Stdev	3,508	5,363	2,031	4,026	3,898	7,474	
Pred. Prof.	*13,170*	*15,511*	*9,592*	*12,365*	*12,853*	*17,151*	*14,097*
p-value	**0.000**	0.586	0.178	**0.000**	**0.000**	0.959	

Retailers obtained lower profits than the predicted values on average. This is an expected outcome because any deviation from the newsvendor quantity reduces the retailer's expected profit. The reduction; however, is not found to be significant. This is mainly due to the existence of the buyback term: Even when the retailer orders more than she should, the loss is small because unsold products are returned to the manufacturer at the buyback price. The manufacturer's profit depends on the stock quantity of the retailer. We observe the manufacturer's profit to be significantly higher than predicted when the retailer overstocked, and significantly lower than predicted when the retailer understocked.

Figure 5.2.3(a)-(f) presents the stock quantities and profit levels for the six pairs separately over time. We observe the individual retailer behavior to be highly variable. Some retailers (such as retailer 3) consistently stocked high quantities, whereas some (such as retailer 1) stocked low. We observe how the retailer's profit variance increases with his stock quantity. Setting a high stock quantity means taking risk: The retailer may win or lose a lot, increasing his profit variance. Retailers 4 and 5, for example, set high stock quantities and ended up losing money in some games. Retailer 4 made loss in four games, averaging $9,219. Retailer 5 made loss in six games, averaging $7,293. These losses explain the difference between retailer 4 and 5's mean and median profit levels. The situation with Retailer 3 is rather different. This retailer was offered very attractive contract parameters (as we will discuss later) ordered high quantities, and made high profits without much risk. Her partner, manufacturer 3, paid the price of offering generous contract parameters with his own profit. The total profit is proportional to the retailer's stock quantity. Pairs in which the retailer stocked low quantities ended up making low total profits.

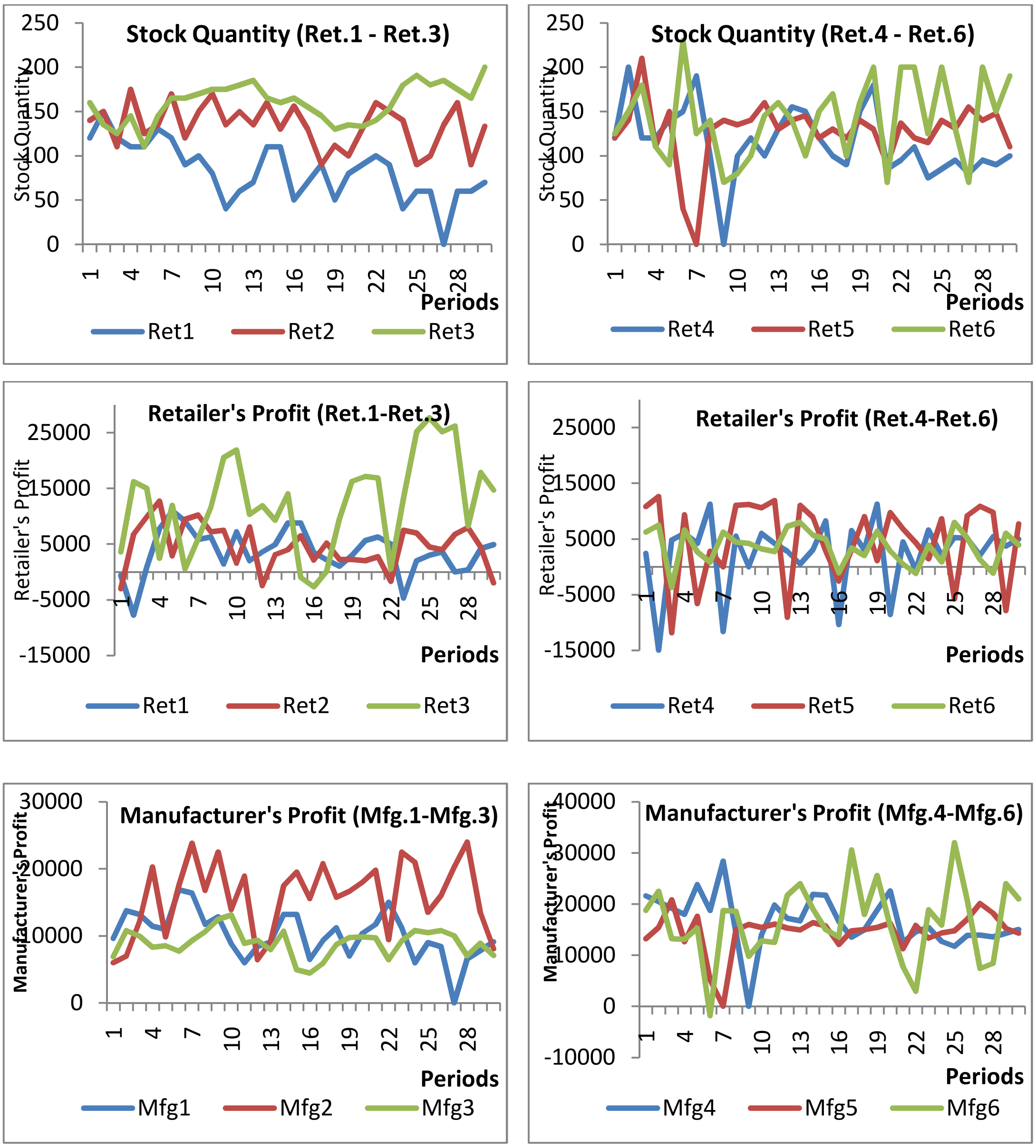


Figure 5.2.3 (a)-(c) Stock Quantities and Profit Levels for the Six Pairs in Experiment b1a

The overstocking behavior of retailers is interesting. Human subjects are known to under-stock in newsvendor experiments under wholesale price contracts (see, Keser and Paleologo 2004). Perhaps, the existence of the buyback term in the contract gives a feeling of excessive safety to the retailers, prompting them to stock more than the best response.

5.2.1.2 Manufacturer's Contract Parameter Decisions

Here we study the manufacturer's contract parameter *(w, b)* decisions. Recall that the contract parameters determine the critical ratio (which determines the newsvendor quantity) and the retailer's expected profit, which is a proxy for contract attractiveness. Figure 5.2.4 (a)-(d) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.3 summarizes the mean values.

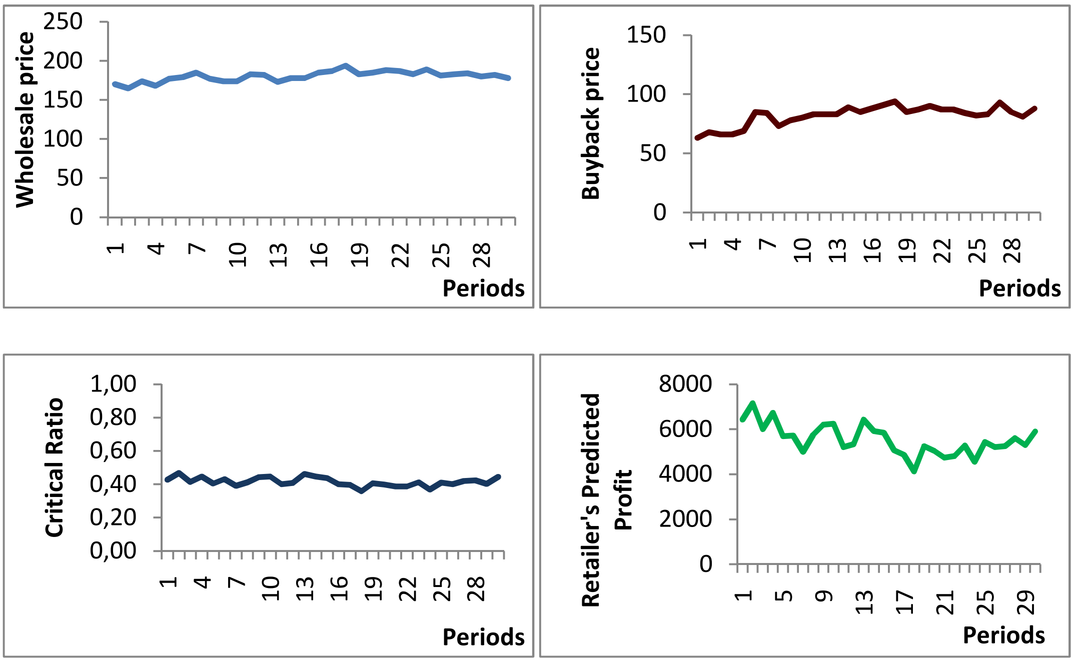


Figure 5.2.4 (a)-(d) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment b1a

Table 5.2.3 Contract Parameters in Experiment b1a

	Wholesale Price	**Buyback Price**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	247	246	0.75	*333*
Mean Data	180	82	0.42	*5,537*
Median Data	182	84	0.41	*5,381*
Stdev Data	7	8	0.03	*673*

We observe that on average, the manufacturers choose lower wholesale prices and much lower buyback prices than the ones in their theoretical optimal solution. Manufacturer-level decisions presented in Table 5.2.4 also confirm this behavior.

Table 5.2.4 Manufacturer-level Decisions in Experiment b1a

	Mfg. Optimal	**Mfg-1**	**Mfg-2**	**Mfg-3**	**Mfg-4**	**Mfg-5**	**Mfg-6**
Wholesale Price w	247	182	193	122	202	172	209
Buyback Price b	246	54	134	54	44	37	165

Figure 5.2.5(a)-(b) below illustrates the retailer's expected profit (i.e., contract attractiveness) over time for all six pairs. We observe that Manufacturer-3 offered very attractive contract parameters, which lead to high stock quantities and high profits for Retailer-3. Manufacturer-2, on the other hand, reduced the desirability of his offered contract over time.

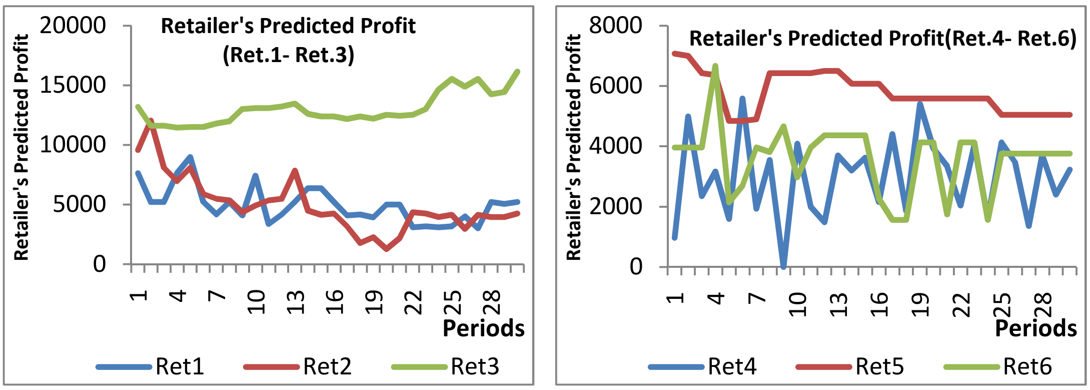


Figure 5.2.5 (a)-(b) Retailer's Predicted Profit in Experiment b1a

Why did the manufacturers not offer their theoretical optimal contract, but offered much lower wholesale price and buyback price values that lead to higher expected profit to the retailer? Possible reasons include the following:

- **Making the necessary calculations:** Theory assumes that the manufacturers will be able to make the related calculations and foresee the expected outcome for every contract they may offer. However, human beings are boundedly rational and they have limited cognitive abilities. Although the decision-support-tool on their screens provides assistance, the subjects may not be able to make these calculations. In particular, determining two contract parameters together may be a difficult task for the manufacturers.

- **Risk- and loss-averse retailers:** Theory assumes that the retailer will accept any contract that provides her a non-negative expected profit. In addition, the theoretical calculations assume a risk-neutral retailer. However, human beings are risk averse and hence, they need to be compensated when they make decisions under risk. In addition, they are loss averse: They weigh losses more heavily than gains in their mind. Hence, a contract that provides only a small positive expected profit may not be accepted by the retailer. Knowing this, the manufacturer may be offering a more attractive contract to the retailer.

- **Fairness:** The theoretical optimal solution provides only 1.5% of the total profit to the retailer, and 98.5% to the manufacturer. Human beings are known to be averse to “unfairness”. In particular, the retailers are not likely to accept such a contract that proposes a very unfair share of profits. The manufacturer himself may not also enjoy being “unfair” to the retailer. Hence, he offers contracts that propose a more equitable sharing of profits.

- **Fear of contract rejection:** Recall that although the manufacturer enjoys the first-mover advantage in the game, the retailer can reject the contract by ordering zero units, and cause both firms to gain zero profits. That is, the retailer has vetoing power in the game. Although we observe contract rejection only in three games out of 180, the fear of rejection is likely to keep the manufacturer from offering unattractive contracts.

- **Retailer's over-stocking bias:** The manufacturer may understand the over-stocking bias of the retailer in the presence of the buyback term in the contract. Hence, he may find it sufficient to offer a relatively low buyback price in his contracts.

5.2.1.3 Changes in Decisions over Time

Next, we aim to understand if and how the subjects' decisions changed over time perhaps, due to learning. To do so, we segment the time horizon into three to compare the results in the initial ten periods with the results in the last ten periods. Table 5.2.5 presents the average-over-subjects results. The p-values of Wilcoxon Signed Rank test are provided in the bottom row of the table.

Table 5.2.5 Mean Values in Three Period Blocks in Experiment b1a

	Stock Quantity			Retailer Profit			Mfg. Profit			Wholesale Price		Buyback Price		Critical Ratio	
Per.	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	**Mean Data**	**Median Data**	**Mean Data**	**Median Data**
1-10	134	130	*121*	5,502	5,016	*6,094*	14,304	14,435	*13,778*	174	174	73	71	0.43	0.43
11-20	129	130	*118*	4,503	4,929	*5,309*	14,411	14,480	*14,257*	183	183	87	86	0.41	0.41
21-30	125	127	*117*	6,046	5,992	*5,209*	13,484	13,710	*14,256*	184	183	86	86	0.41	0.41
p-value		0.083			0.508			0.203			**0.007**		**0.007**		0.114

We observe that overall, both the wholesale price and the buyback price increased significantly from the first ten periods to the last ten periods. The critical ratio saw a decrease, albeit not significant. The attractiveness of the contracts, as indicated by the retailer's predicted profit also decreased. These led to a reduction in stock quantity, triggering reduction in manufacturer's profit. The retailer's profit, on the other hand increased, but not significantly.

Next we look into the subject-level results of Table 5.2.6 to gain a deeper understanding. Again, we observe serious level of intra-subject variation. Hence, one should be careful in interpreting the average-over-retailer type results in the literature, including ours.

Table 5.2.6 Subject-level Changes over Time in Experiment b1a

	Period	**Pair-1**	**Pair-2**	**Pair-3**	**Pair-4**	**Pair-5**	**Pair-6**
Q	**1-10**	113	145	150	119	131	130
	11-20	73	130	160	130	136	143
	21-30	70	129	170	105	129	154
	p-value	**0.005**	0.355	**0.041**	0.066	0.919	0.284
Retailer Profit	**1-10**	4,114	6,522	10,974	1,505	5,550	3,554
	11-20	4,343	3,312	8,491	2,072	4,579	4,221
	21-30	2,744	4,130	17,583	3,916	4,498	2,733
	p-value	0.444	0.093	0.241	0.333	0.799	0.444
Mfg. Profit	**1-10**	12,561	14,978	9,776	19,856	14,588	14,101
	11-20	9,432	15,823	8,059	18,378	15,197	19,579
	21-30	9,422	16,805	9,057	13,760	15,448	15,917
	p-value	0.086	0.445	0.444	0.093	0.859	0.721
Retailer Predicted Profit	**1-10**	6,083	7,083	12,078	2,821	6,070	3,881
	11-20	4,796	4,010	12,646	3,174	5,996	3,504
	21-30	4,008	3,821	14,345	2,935	5,262	3,413
	p-value	**0.011**	**0.005**	**0.007**	0.799	**0.028**	0.799
w	**1-10**	173	174	128	202	167	203
	11-20	184	204	127	201	171	210
	21-30	190	203	112	203	178	214
	p-value	**0.019**	**0.008**	**0.007**	0.813	**0.014**	0.117
b	**1-10**	58	110	54	42	25	140
	11-20	56	151	63	44	39	168
	21-30	47	142	45	45	45	187
	p-value	**0.033**	**0.035**	**0.015**	0.44	**0.005**	**0.014**

Pair-1 is interesting. Manufacturer-1 decreased the attractiveness of the contract over time by decreasing the buyback price, and increasing the wholesale price. Retailer-1 responded by decreasing the stock quantity, which caused both firms' profits to decrease. This is an example of a lose-lose outcome. Pair-2 is similar. Pair-3, on the other hand, is just the opposite: The attractiveness of the contract, which was already good, increases even more over time. This leads to higher stock quantities and very high retailer profits. For this pair, it is the manufacturer who makes the sacrifice.

Figure 5.2.6 depicts the mean (over manufacturers) contract parameters *(w,b)* . The numbers denote the periods. Note that the manufacturer's optimal contract *(w*=247, b*=246)* is too large to be shown in this figure.

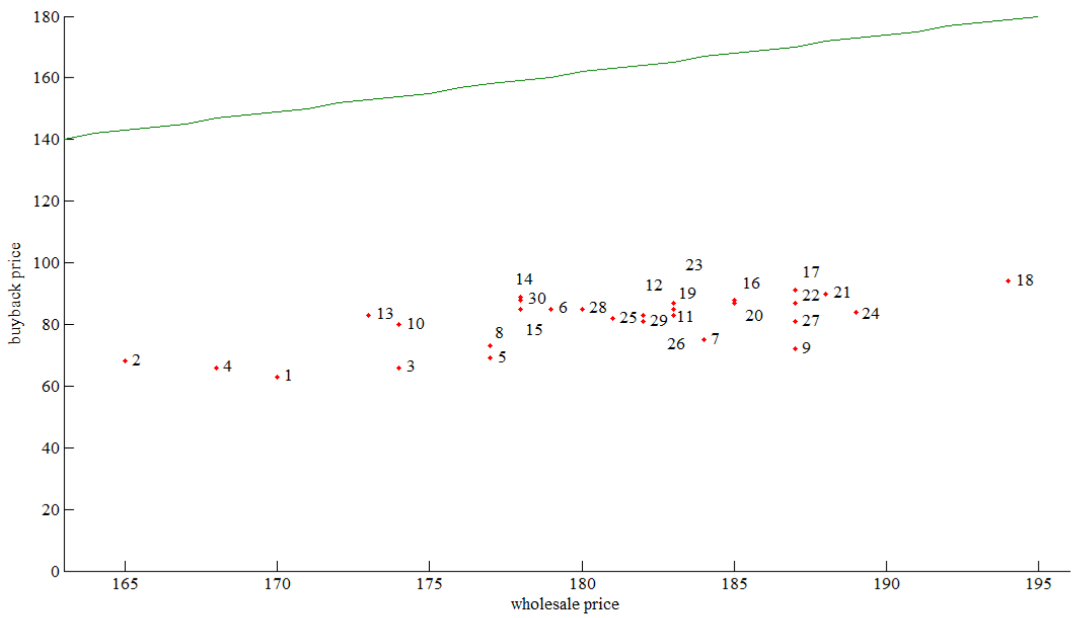


Figure 5.2.6 Mean Contract Parameters (w,b) in Experiment b1a

The changes seem to be in a larger scale in the first ten periods. In the last ten periods, however, the manufacturers seem to have determined their strategy. We came up with the idea that the subjects might stick to a certain *(w,b)* pair towards the end of the game as a result of their strategy or boredom. We wanted to understand if the manufacturers' contract decisions "stabilized" towards the end of the interaction. To this end, we analyzed the autocorrelations of the *(w,b)* decisions for the first and the last ten periods. If a subject stabilizes his decisions, one expects autocorrelation in the last 10 periods relative to the first 10 periods. As shown in Appendix H, we could not find evidence to support this hypothesis.

5.2.1.4 Rejected Contracts

There are only three games (out of 180) where the retailers rejected the contract by setting zero stock quantity. These three contracts are shown with red circles in Figure 5.2.7, which plots the retailer's expected profit as a function of the contract parameters. We observe that the rejected contracts are among those that have high wholesale price and low buyback price, leading to low expected profit. Table 5.2.7 provides the details. We note that two of the three rejected contracts have positive predicted profit for the retailer, but not at high levels.

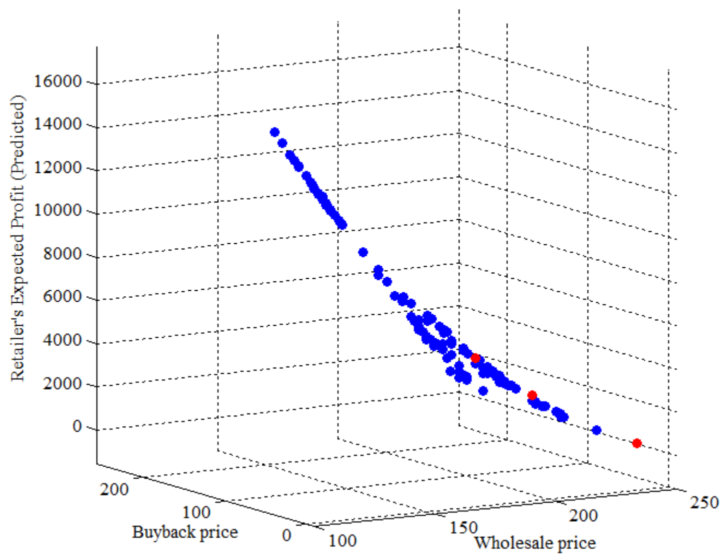


Figure 5.2.7 Rejected and Accepted Contracts in Experiment b1a

Table 5.2.7 Rejected Contracts with Predicted Results in Experiment b1a

Period of Rejection	**Retailer Number**	**w**	**b**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
27	1	200	20	81	*12,104*	*3,013*
8	4	250	40	40	*8,000*	*0*
7	5	180	30	100	*12,767*	*4,892*

5.2.2 Experiment b1b

Experiment b1b has eight manufacturers and eight retailers. Contract rejection is observed in fifteen games.

5.2.2.1 Retailer's Stock Quantity Decision and Firms Profits

Figures 5.2.8 (a)-(c) present the mean stock quantity and the firms' profits across eight games over 30 periods. Table 10 summarizes the comparison.

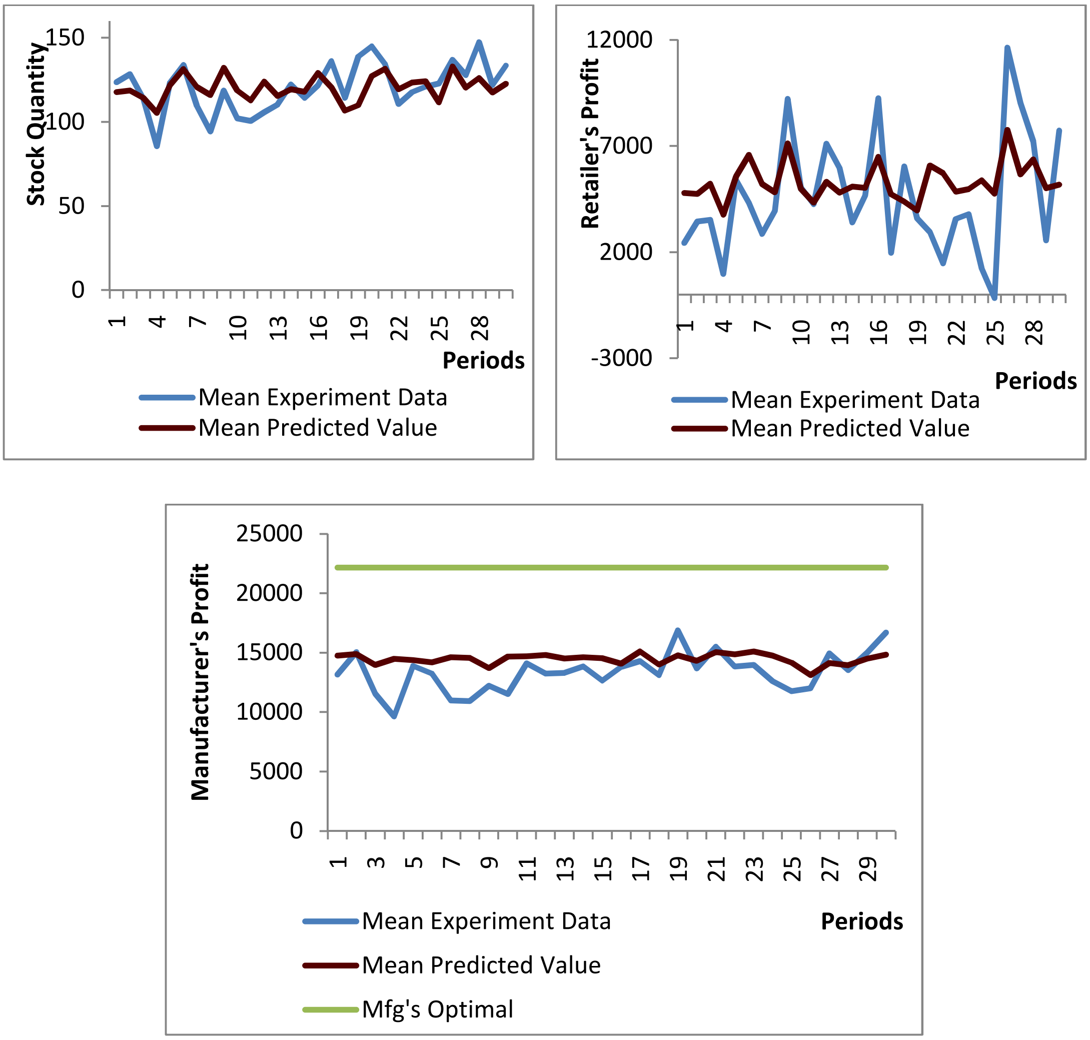


Figure 5.2.8 (a)-(c) Stock Quantity and Firms Profits in Experiment b1b

Table 5.2.8 Stock Quantities and Firms Profits in Experiment b1b

	Stock Quantity			**Retailer's Profit**			**Manufacturer's Profit**		
	Data	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**
Mean	121	*120*		4,616	*5,291*		13,362	*14,467*	
Median	122	*120*	0.992	3,868	*5,060*	0.111	13,416	*14,540*	0.001
St.dev.	15	*7*		2,790	*888*		1,638	*446*	

We observe that retailers on average stocked slightly higher than the predicted quantities, which is consistent with Experiment b1a. However, the difference between data and predicted values is quite small compared to Experiment b1a. We cannot speak of a significant "overstocking" in this experiment. However, we observe from Figure 5.2.8(a) that the retailers understocked in the initial periods, but overstocked in the latter ones.

With these stock quantities, retailers obtained quite lower profits than predicted. However, the difference is not significant. Although the mean stock quantity is close to the mean predicted value, there exist variations in individual decisions over periods, which cause reduction in profit. Recall that all deviations from the predicted (newsvendor) quantity lead to reduction in retailer's expected profit. We observe that manufacturer's profit is lower than his predicted profit, particularly in the earlier periods where the retailer understocks. Unlike Experiment b1a, the ordering behavior of the retailer reduces the manufacturer's profit significantly.

5.2.2.2 Manufacturer's Contract Parameter Decisions

Figure 5.2.9 (a)-(d) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.9 summarizes the results.

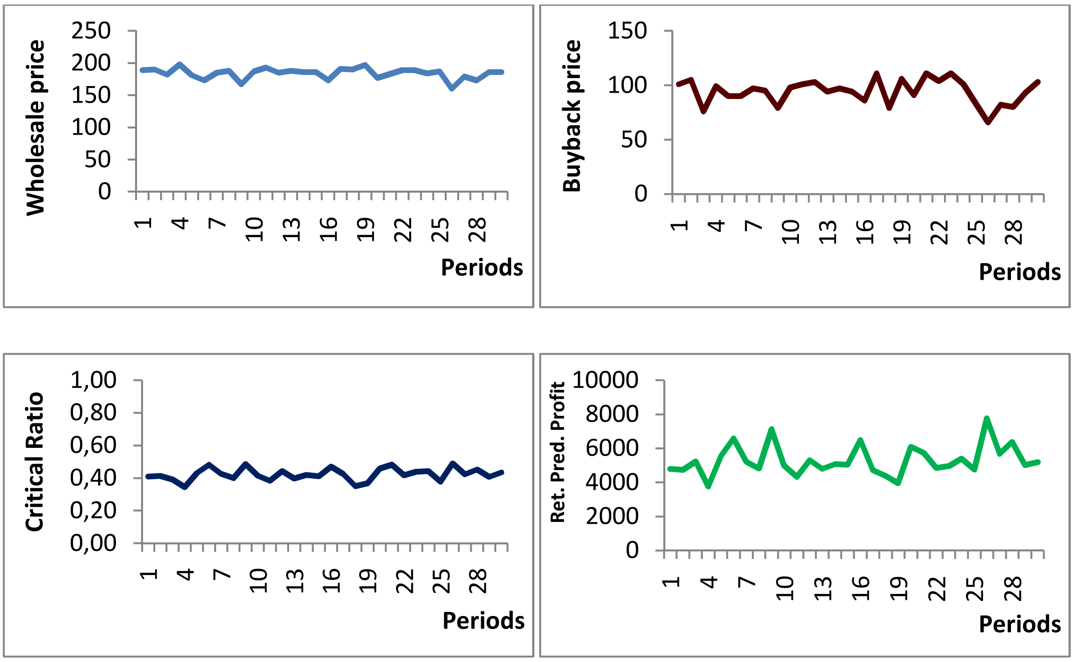


Figure 5.2.9 (a)-(d) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment b1b

Table 5.2.9 Contract Parameters in Experiment b1b

	Wholesale Price (Data)	**Buyback Price (Data)**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	247	246	0.75	*333*
Mean	184	94	0.42	*5,291*
Median	186	96	0.42	*5,060*
Stdev	8	11	0.04	*888*

We observe that the contract parameters are overall stable over time. There has been some fluctuation in the buyback price, leading to a fluctuation in the retailer's predicted profit. On average, the manufactures choose lower wholesale prices and much lower buyback prices than the optimal values. This is similar to Experiment b1a. The chosen parameters lead to a low critical ratio, causing low stock quantities relative to the optimal solution. Retailer's predicted profit comparison indicates that the manufacturers are offering much more attractive contracts than the ones in the optimal solution. This leads to a more equitable sharing of profits between the firms.

5.2.2.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.2.10, we present the subjects' mean decisions and profits in three period blocks consisting of periods 1-10, periods 11-20, and periods 21-30. To test for statistical significance, we compare the data of the first 10 periods with the last 10 periods.

Table 5.2.10 Mean Values in Three Period Blocks in Experiment b1b

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**b**	**Critical Ratio**
	Data	***Pred.***	***Data***	***Pred.***	***Data***	***Pred.***	**Data**	**Data**	**Data**
Per. 1-10	113	*120*	4,118	*5,280*	12,216	*14,416*	184	93	0.42
Per. 11-20	121	*118*	4,922	*5,021*	13,888	*14,547*	187	96	0.41
Per. 21-30	127	*123*	4,808	*5,571*	13,982	*14,439*	182	93	0.44
p-value	**0.038**		0.333		**0.028**		0.443	0.878	0.285

We observe that the retailers understocked in the initial periods leading to quite poor profits. In periods 11-20, the retailers slightly overstocked. Note that the realized profit is close to the predicted profit. In the last periods, the retailers overstocked slightly more. However, because the mean predicted quantity increased, mean predicted profit increased to 5,571. This time, the overstocking policy fell short of reaching that profit. When we check the individual data, we observe that this is because of the increased variation in individual decisions. The overstocking strategy is consistent with Experiment b1a.

We observe no significant change in wholesale price, buyback price, and the implied critical ratio from the first ten periods to the last ten periods. However, manufacturer's profit increases significantly. This is not surprising given that the manufacturer's profit depends not only on the contract parameters, but also on the retailer's stock quantity decision. Although not significant, the increase in retailer's predicted profit indicates that the manufacturer offers more favorable contract parameters in the last periods. This change and the retailer's switch to an overstock strategy cause the retailer to order more, increasing the manufacturer's profit.

5.2.2.4 Rejected Contracts

Table 5.2.11 summarizes the data of the games in which the retailer rejected the contract. We observe that the most of the rejections are due to one single player (retailer 2); hence, rejection is not a common retailer strategy. Given that rejections are concentrated in the last periods, the cause of rejections is not likely to be "strategic signaling".

Table 5.2.11 Rejected Contracts with Predicted Results in Experiment b1b

Period of Rejection	**Retailer Number**	**w**	**b**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
1	2	225	180	108	*16,673*	*1,840*
18	2	230	205	124	*18,528*	*1,639*
20	2	231	198	109	*17,271*	*1,414*
22	2	246	239	109	*18,352*	*297*
23	2	245	235	103	*17,643*	*357*
24	2	230	225	192	*20,862*	*2,318*
25	2	230	225	192	*20,862*	*2,318*
26	2	200	170	159	*17,484*	*4,959*
26	3	220	150	97	*15,192*	*2,045*
25	4	195	180	189	*16,875*	*6,299*
26	4	190	189	227	*14,391*	*8,006*
27	4	200	199	226	*15,768*	*6,656*
29	6	200	100	103	*14,433*	*3,567*
30	6	200	100	103	*14,433*	*3,567*
6	7	189	80	108	*14,049*	*4,500*

Retailers are more likely to reject contracts that provide low predicted profit for them, which is not surprising. However, all of the rejected contracts would theoretically result in nonnegative profit for the retailer. By rejecting such a contract, the retailer gave up an expected positive profit. Risk aversion may explain this behavior. Although the contract provides positive expected profit, losses are also possible which causes risk for the retailer.

5.2.3 Experiment b2a

Experiment b2a has eight manufacturers and eight retailers. Contract rejection is observed in two games.

5.2.3.1 Retailer's Stock Quantity Decision and Firms Profits

Figure 5.2.10(a)-(c) present the mean stock quantity and the firms' profits across eight games over 30 periods. Table 5.2.12 summarizes the comparison.

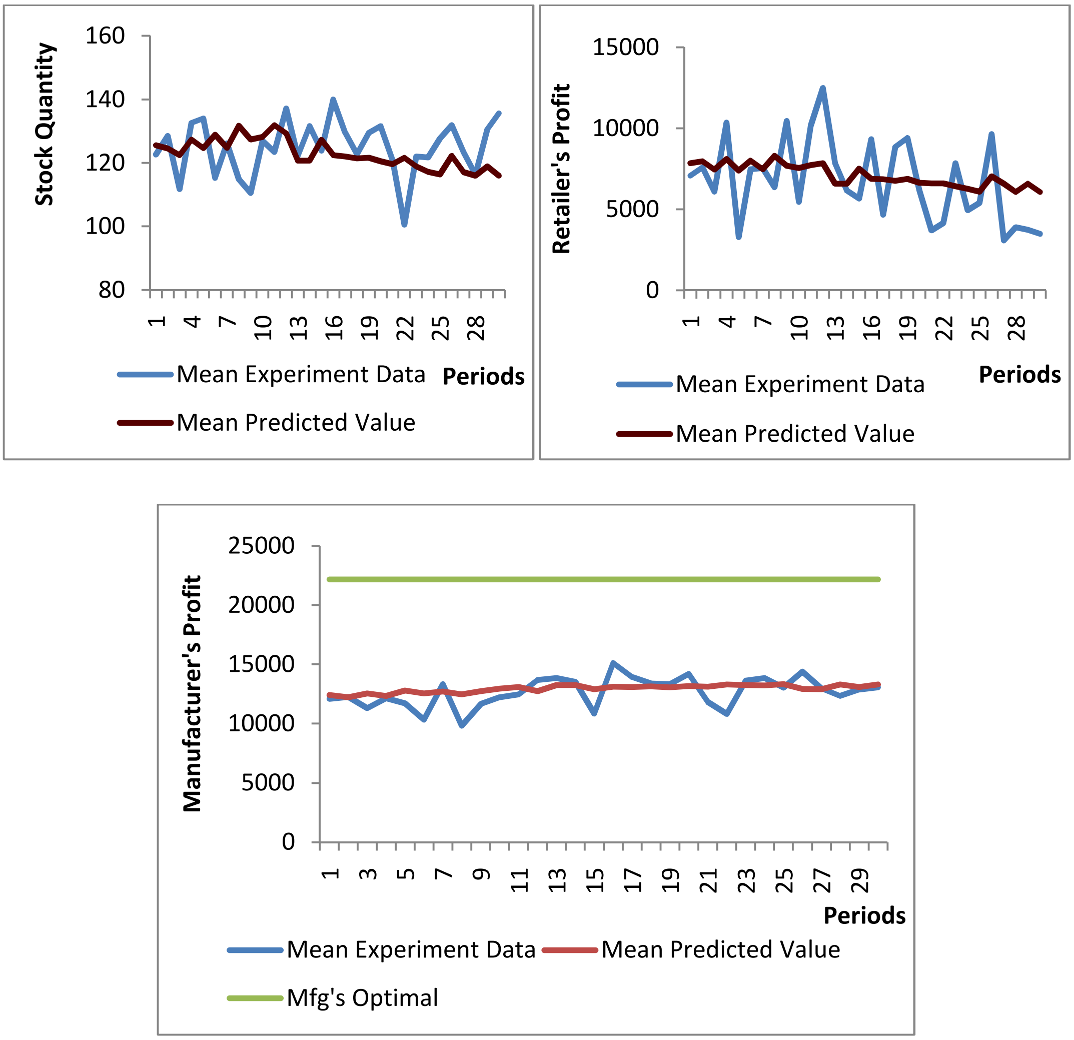


Figure 5.2.10 (a)-(c) Stock Quantity and Firms Profits in Experiment b2a

Table 5.2.12 Stock Quantities and Firms Profits in Experiment b2a

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	125	*123*		6,736	*7,071*		12,667	*12,944*	
Median	125	*122*	0.173	6,271	*6,869*	0.289	12,924	*13,072*	0.196
St.dev.	9	*5*		2,530	*669*		1,258	*321*	

We observe that retailers on average order slightly higher than the predicted average. However, the difference between data and predicted values are quite small. We cannot speak of a significant "overstocking" in this experiment. This outcome does not result in a significant difference between the realized profit values and the predicted for the manufacturer or the retailer.

5.2.3.2 Manufacturer's Contract Parameter Decisions

Figure 5.2.11 (a)-(d) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.13 summarizes the comparison.

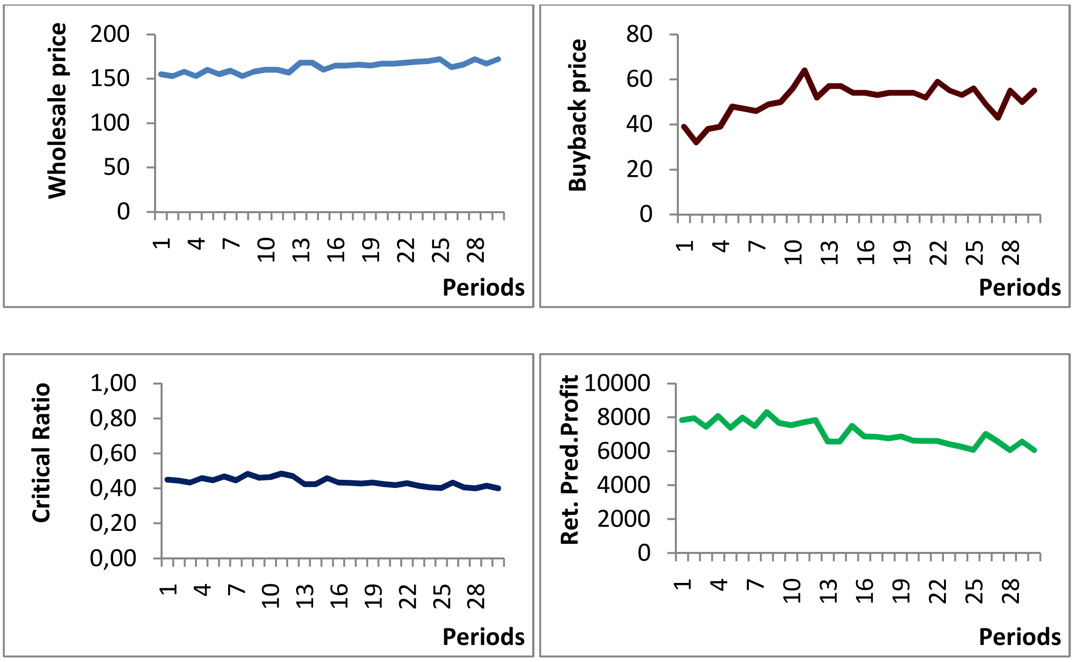


Figure 5.2.11 (a)-(d) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment b2a

Table 5.2.13 Contract Parameters in Experiment b2a

	Wholesale Price (Data)	**Buyback Price (Data)**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	247	246	0.75	*333*
Mean	163	51	0.44	*7,071*
Median	165	53	0.43	*6,878*
Stdev	6	7	0.02	*668*

Similar to long run buyback experiments, the manufactures choose lower wholesale prices and much lower buyback prices than the ones in their theoretical optimal solution.

5.2.3.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.2.14, we present the subjects' mean decisions and profits in three period blocks consisting of periods 1-10, periods 11-20, and periods 21-30 with p-values of the Wilcoxon Signed Rank Test.

Table 5.2.14 Mean Values in Three Period Blocks in Experiment b2a

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**b**	**CR**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**	**Data**
Per. 1-10	122	*127*	7,162	*7,770*	11,688	*12,576*	156	44	0.46
Per. 11-20	129	*124*	8,070	*7,020*	13,432	*13,084*	164	55	0.44
Per. 21-30	123	*118*	4,977	*6,425*	12,883	*13,177*	169	53	0.41
p-value	0.878		**0.047**		0.059		**0.005**	**0.028**	**0.005**

We observe that the manufacturers significantly increase their wholesale prices and their buyback price over time. However, they do not increase the buyback price as much as the wholesale price. Therefore, they offer less attractive contracts in the last ten periods as indicated in the retailer's predicted profit values. The retailers do not respond to this increase and they do not decrease the stock quantity significantly. As a result, the retailers gain significantly lower profits in the last ten periods in comparison to the first ten periods.

5.2.3.4 Rejected Contracts

Table 5.2.15 summarizes the data of the games in which the retailer rejected the contract.

Table 5.2.15 Rejected Contracts with Predicted Results in Experiment b2a

Period of Rejection	**Retailer Number**	**w**	**b**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
11	4	210	10	72	*11,440*	*0*
3	7	200	10	80	*11,895*	*2,970*

Retailer 4 rejects a contract where he would not gain positive profit whereas retailer 7 rejects a contract with an expected profit of 2,970. Both of the rejections can be acceptable as 0 and 2,970 are low profit values for the retailer.

5.2.4 Experiment b2b

Experiment b2b has eight manufacturers and eight retailers. Contract rejection is observed in thirteen games.

5.2.4.1 Retailer’s Stock Quantity Decision and Firms Profits

Figure 5.2.12 (a)-(c) present the mean stock quantity and the firms’ profits across eight games over 30 periods. Table 5.2.16 summarizes the comparison.

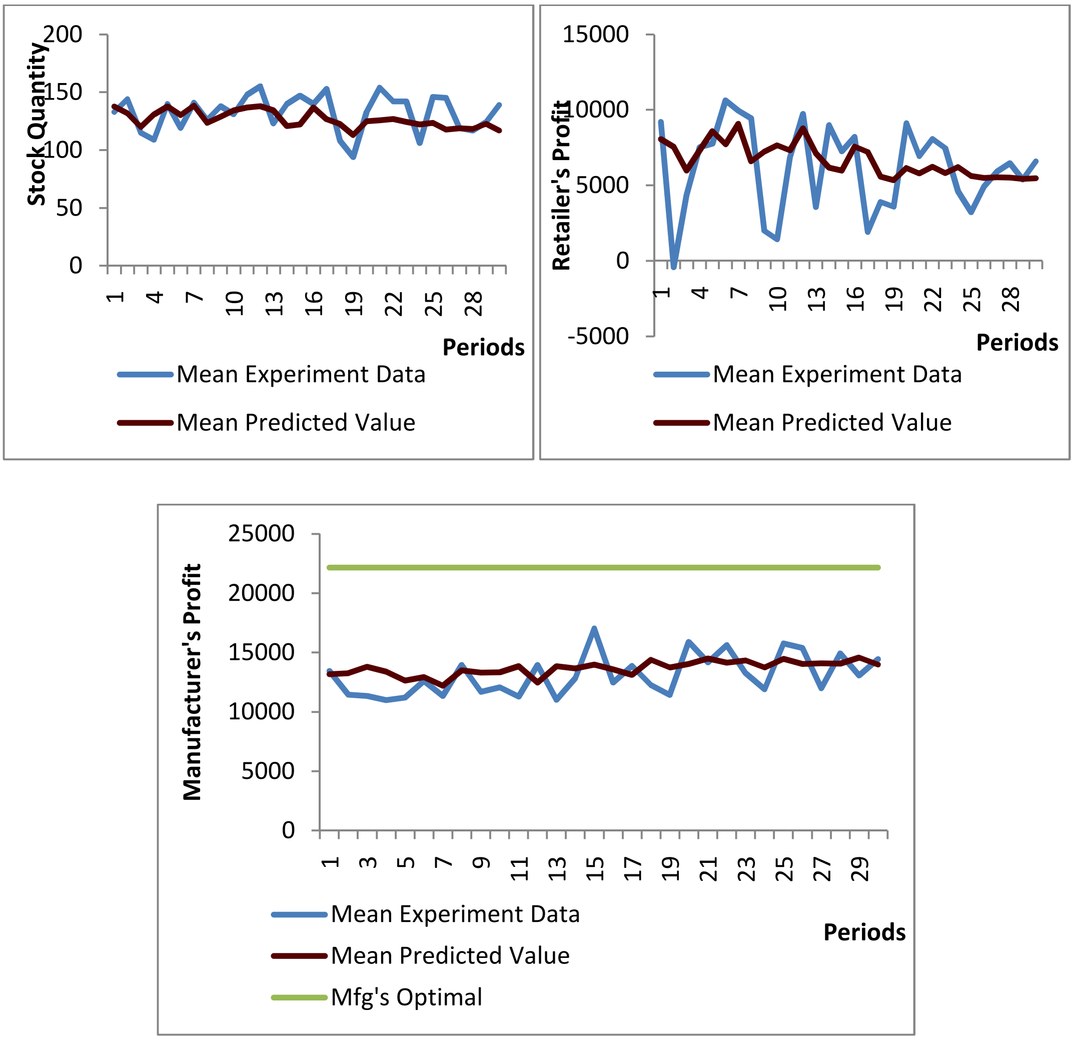


Figure 5.2.12 (a)-(c) Stock Quantity and Firms Profits in Experiment b2b

Table 5.2.16 Stock Quantities and Firms Profits in Experiment b2b

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	132	*127*		6,152	*6,672*		13,090	*13,672*	
Median	139	*125*	**0.050**	6,720	*6,230*	0.781	12,720	*13,762*	**0.047**
St.dev.	16	*7*		2,857	*1,107*		1,715	*604*	

We observe an overstocking behavior of the retailers on the average. The overstocking did not result in an increase in the manufacturer's profit, though. The retailer's profit comparison is interesting. The observed data is higher if one compares the median values, whereas the predicted value is higher in one compares the mean values. This difference is due to the existence of some very low retailer profit realizations.

5.2.4.2 Manufacturer's Contract Parameter Decisions

Figures 5.2.13 (a)-(d) illustrate the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.17 summarizes the comparison.

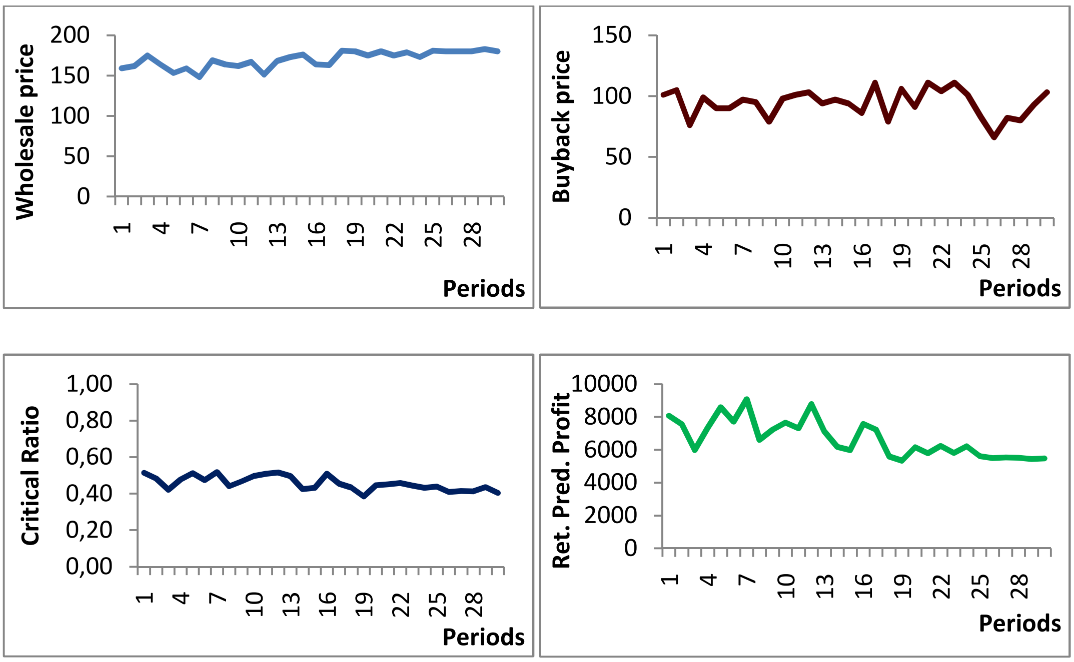


Figure 5.2.13 (a)-(d) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment b2b

Table 5.2.17 Contract Parameters in Experiment b2b

	Wholesale Price (Data)	**Buyback Price (Data)**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	247	246	0.75	*333*
Mean	170	76	0.46	*6,672*
Median	173	75	0.45	*6,230*
Stdev	10	12	0.04	*1,107*

We observe that on average, the manufactures choose lower wholesale prices and much lower buyback prices than the ones in their theoretical optimal solution. This is a parallel result with the other buyback experiments.

5.2.4.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.2.18, we present the subjects' mean decisions and profits in three period blocks consisting of periods 1-10, periods 11-20, and periods 21-30. To test for statistical significance, we compare the data of the first 10 periods with the last 10 periods.

Table 5.2.18 Mean Values in Three Period Blocks in Experiment b2b

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**b**	**CR**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**	**Data**
Per. 1-10	130	*131*	6,185	*7,577*	12,007	*13,148*	162	66	0.48
Per. 11-20	134	*128*	6,312	*6,726*	13,209	*13,670*	170	76	0.46
Per. 21-30	133	*122*	5,958	*5,713*	14,054	*14,197*	179	85	0.43
p-value	0.575		0.959		**0.005**		**0.005**	**0.005**	0.285

Similar to Experiment b2a, both the wholesale price and the buyback price increase significantly from the first ten periods to last ten periods. This results in a decrease in the retailer's predicted profit level. Although the predicted stock quantity decreases from the first block to the last, we observe an increase in the stock quantity (though not significant). The manufacturers benefit from this increase in stock quantity, and they gain significantly higher profits in the last ten periods. Different from Experiment b2a, the retailer's profit is higher than predicted in the last ten periods as a result of the high profits of one single retailer who increased the average.

5.2.4.4 Rejected Contracts

Table 5.2.19 summarizes the data of the games in which the retailer rejected the contract.

Table 5.2.19 Rejected Contracts with Predicted Results in Experiment b2b

Period of Rejection	**Retailer Number**	**w**	**b**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
5	6	225	140	83	*13,858*	*1,530*
7	6	200	130	119	*15,715*	*3,965*
8	6	190	108	120	*14,994*	*4,791*
12	6	195	145	140	*16,433*	*4,924*
13	6	170	20	106	*12,498*	*5,818*
14	6	185	140	152	*15,896*	*6,236*
18	6	225	30	62	*10,740*	*1,259*
20	6	190	35	93	*12,761*	*3,969*
19	4	240	150	59	*11,061*	*491*
2	3	165	30	113	*12,613*	*6,494*
4	3	225	125	78	*13,165*	*1,465*
5	3	240	215	94	*16,225*	*668*
11	1	160	15	113	*12,193*	*6,847*

We observe that most 8 of the 14 rejections are due to a single retailer (retailer 6). Hence, contract rejection is not a widespread strategy among retailers. This retailer rejected contracts that offered an expected profit level as high as 6,236, which is quite high.

5.2.5. Experiment w1a

Experiment w1a has eight manufacturers and eight retailers. Contract rejection is observed in five games.

5.2.5.1 Retailer's Stock Quantity Decision and Firms Profits

Figures 5.2.4 (a)-(c) present the mean stock quantity and the firms' profits across eight games over 30 periods. Table 5.2.20 summarizes the comparison.

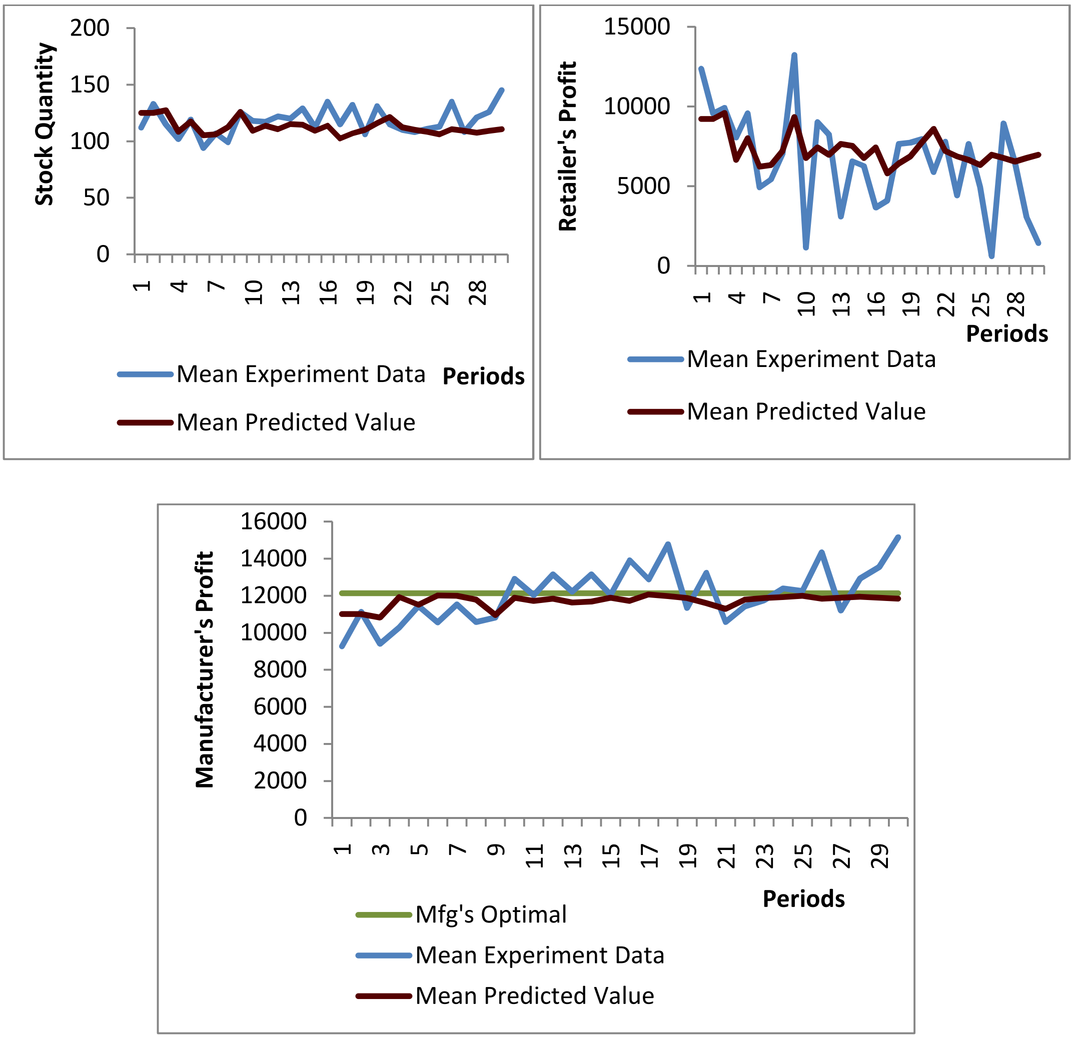


Figure 5.2.14 (a)-(c) Stock Quantity and Firms Profits in Experiment w1a

Table 5.2.20 Stock Quantities and Firms Profits in Experiment w1a

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	118	*113*		6,554	*7,295*		12,076	*11,707*	
Median	116	*111*	**0.032**	6,796	*6,977*	0.309	12,046	*11,843*	0.861
St.dev.	12	*7*		3,069	*995*		1,479	*344*	

Similar to buyback experiments, we observe overstocking behavior of the retailers. This behavior is also illustrated in Figure 5.2.15, which compares the mean experiment data and mean predicted value.

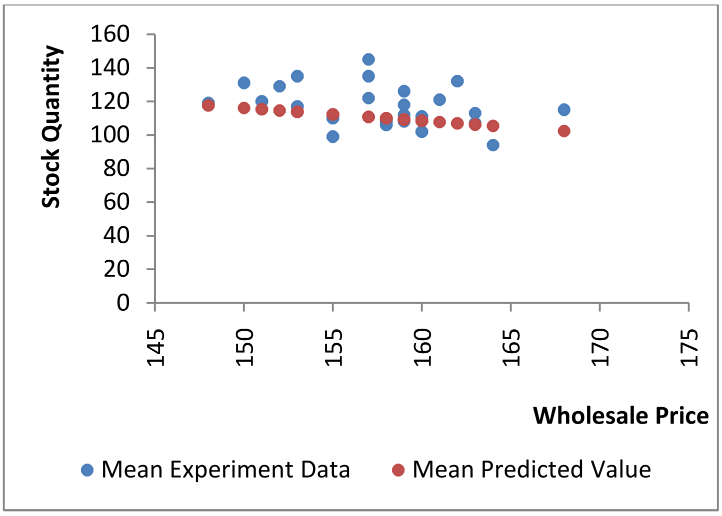


Figure 5.2.15 Comparison of *Q(w,b)* and *Q*(w,b)* in Experiment w1a

The profits of the retailer and the manufacturer are not significantly different from the predicted outcomes. But we observe a variance in the retailer's profit. We study the subject-level results to gain a more detailed understanding. Table 5.2.21 (a)-(c) presents the results by manufacturer-retailer pairs. We observe four of the eight retailers to over-stock significantly, whereas two of them stocked significantly less than predicted.

Table 5.2.21 (a)-(c) Stock Quantities and Firms Profits in Experiment w1a

Stock Quantity	Ret-1	Ret-2	Ret-3	Ret-4	Ret-5	Ret-6	Ret-7	Ret-8	Avr.
Mean Data	123	97	85	119	96	126	142	149	118
Median Data	123	99	80	112	100	120	140	152	
Predicted	*103*	*100*	*124*	*124*	*122*	*105*	*117*	*110*	*113*
p-value	**0.000**	0.629	**0.000**	0.267	**0.000**	**0.000**	**0.001**	**0.000**	

Ret. Profit	Ret-1	Ret-2	Ret-3	Ret-4	Ret-5	Ret-6	Ret-7	Ret-8	Avr.
Mean Data	3,801	6,127	7,937	8,086	7,484	4,134	6,196	8,944	6,554
Median Data	4,450	4,974	8,075	9,400	8,838	7,450	10,178	10,048	
Stdev	7,849	8,075	5,526	6,398	5,405	8,799	10,473	8,900	
Pred. Prof.	*5,983*	*6,523*	*9,055*	*9,076*	*8,759*	*6,199*	*8,025*	*6,919*	*7,295*
p-value	0.136	0.441	**0.021**	0.926	0.766	**0.004**	**0.008**	**0.033**	

Mfg. Profit	Mfg.-1	Mfg.-2	Mfg.-3	Mfg.-4	Mfg.-5	Mfg.-6	Mfg.-7	Mfg.-8	Avr.
Mean Data	14,249	10,560	7,349	10,538	8,688	14,379	13,959	16,006	12,076
Median Data	14,675	10,240	7,000	10,352	8,952	13,525	13,475	16,730	
Stdev	3,139	4,468	3,195	2,544	1,856	3,450	4,049	3,506	
Pred. Prof.	*11,851*	*9,964*	*10,941*	*11,009*	*11,152*	*11,937*	*11,410*	*11,775*	*11,707*
p-value	**0.000**	0.787	**0.000**	0.262	**0.000**	**0.000**	**0.001**	**0.000**	

We observe the individual retailer behavior to be highly variable. Some retailers (such as retailer 1) consistently stocked high quantities, whereas some (such as retailer 3) stocked low. We observe how the retailer's profit variance increases with his stock quantity. Retailer 6, for example, ordered significantly higher than the predicted. As she ordered higher than she should, the retailer's profit is significantly lower than the predicted. Manufacturer 6, on the other hand, benefits from the overstocking behavior of the retailer and gains significantly higher.

The following figures, Figure 5.2.16(a)-(f), we see the subject based differences more clearly. The outcomes highly depend on individual choices. Those figures illustrate once again that results based on average data need to be used with caution when predicting individual outcomes.

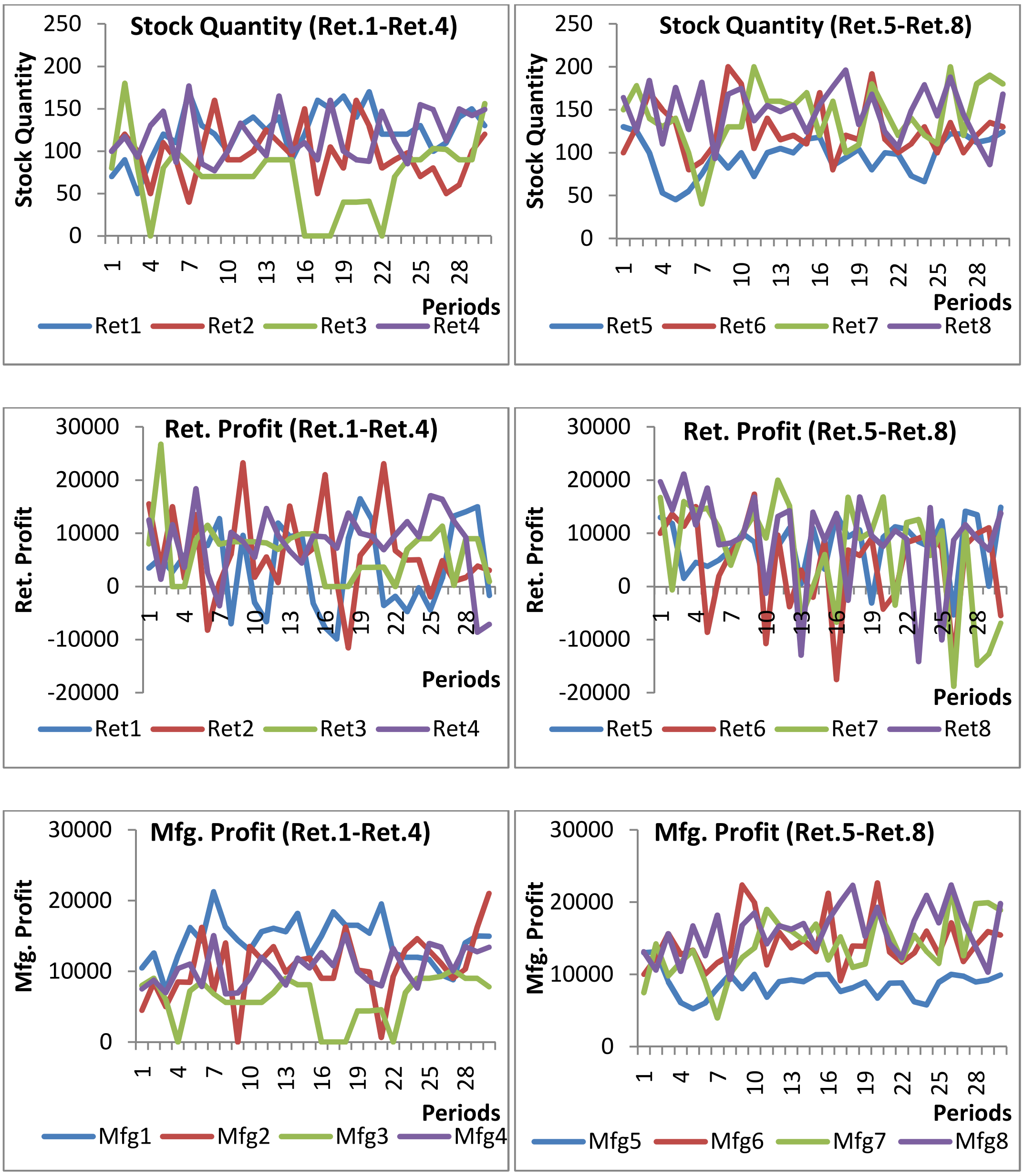


Figure 5.2.16 (a)-(f) Stock Quantities and Profit Levels for the Six Pairs in Experiment w1a

5.2.5.2 Manufacturer's Contract Parameter Decisions

Here we study the manufacturer's contract parameter (*w, b)* decisions. Figures 5.2.17 (a)-(c) illustrate the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.22 summarizes the mean values.

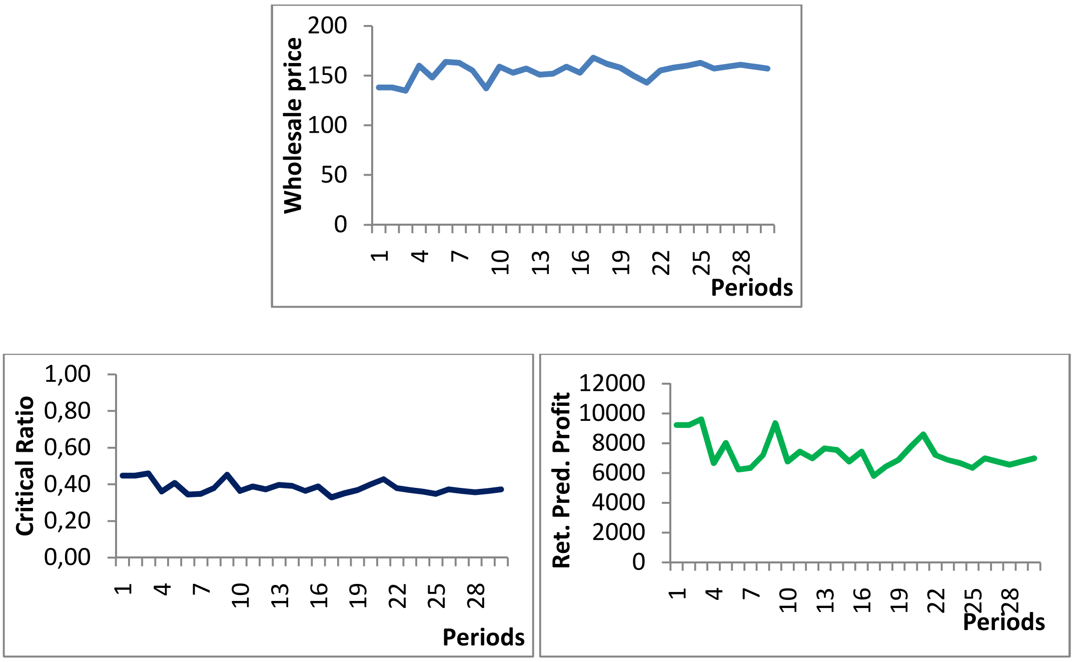


Figure 5.2.17 Wholesale Price, Critical Ratio and Retailer's Expected Profit in Experiment w1a

Table 5.2.22 Contract Parameters in Experiment w1a

	Wholesale Price	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	176	0.75	*5,011*
Mean Data	154	0.38	*7,295*
Median Data	157	0.37	*6,977*
Stdev Data	9	0.03	*995*

We observe that on average, the manufactures choose lower wholesale prices than the ones in their theoretical optimal solution, 176. Manufacturer-level decisions presented in Table 5.2.23 also confirm this behavior.

Table 5.2.23 Manufacturer-level Decisions in Experiment w1a

	Mfg. Optimal	**Mfg-1**	**Mfg-2**	**Mfg-3**	**Mfg-4**	**Mfg-5**	**Mfg-6**	**Mfg-7**	**Mfg-8**
w	176	167	172	140	139	142	165	148	158

The retailer's predicted profit that the manufacturer offers has variations throughout the experiment as seen in Figure 5.2.18 (a)-(b). Those figures show us the variability caused due to individual differences. For instance; we observe that manufacturer 2 offers attractive contracts for the retailer at the end of first ten and last ten periods. In those periods, the manufacturer gains low profits. Manufacturer 6 offers unattractive contracts where the retailer's predicted profit is lower.

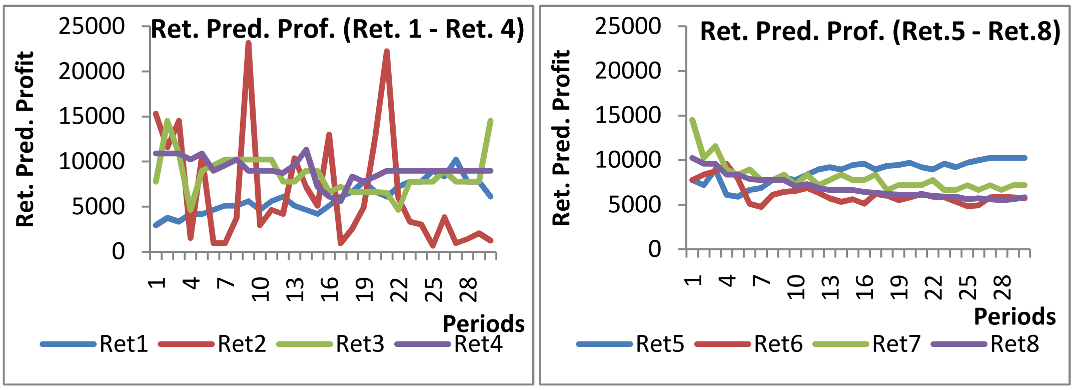


Figure 5.2.18 (a)-(b) Retailer's Predicted Profit in Experiment w1a

5.2.5.3 Changes in Decisions over Time

As shown in Table 5.2.24, we do not observe a significant change in the wholesale price or the stock quantity over time. The critical ratio saw a decrease, albeit not significant. The attractiveness of the contracts, as indicated by the retailer's predicted profit also decreased. These would normally lead to a reduction in stock quantity, triggering reduction in manufacturer's profit as observed in Experiment b1a. However, the retailer increases her stock quantity despite the less attractive contract offers and this results in a significant decrease in her profit over time. The manufacturer benefits from the increasing stock quantity decisions of the retailer.

Table 5.2.24 Mean Values in Three Period Blocks in Experiment w1a

	Stock Quantity			Retailer Profit			Mfg. Profit			Wholesale Price		Critical Ratio	
Per.	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	***Mean Pred.***	**Mean Data**	**Median Data**	**Mean Data**	**Median Data**
1-10	113	114	*116*	8,120	8,796	*7,853*	10,794	10,695	*11,492*	150	152	0.4	0.39
11-20	122	121	*111*	6,427	7,108	*7,066*	12,877	13,020	*11,800*	156	155	0.37	0.38
21-30	119	114	*111*	5,114	5,409	*6,966*	12,559	12,326	*11,828*	157	159	0.37	0.37
p-value		0.173			**0.028**			**0.009**			0.086		0.086

Next we look into the subject-level results of Table 5.2.25 to gain a deeper understanding. Again, we observe serious level of intra-subject variation.

Table 5.2.25 Subject-level Changes over Time Results in Experiment w1a

	Period	Pair-1	Pair-2	Pair-3	Pair-4	Pair-5	Pair-6	Pair-7	Pair-8
Q	**1-10**	105	96	91	111	87	135	124	150
	11-20	136	107	70	116	97	127	151	155
	21-30	129	88	92	129	104	118	151	140
	p-value	0.072	0.442	0.233	0.240	0.202	0.169	0.123	0.445
Retailer Profit	**1-10**	4,510	7,273	9,800	7,057	6,433	6,576	10,881	12,607
	11-20	4,178	5,890	7,307	9,457	7,297	1,573	8,148	8,216
	21-30	2,715	5,218	6,564	7,743	8,722	4,254	-440	6,010
	p-value	0.241	0.721	0.674	0.878	0.386	0.285	**0.047**	0.285
Mfg. Profit	**1-10**	13,790	8,577	6,922	9,028	8,867	14,075	10,554	14,198
	11-20	15,948	11,286	6,657	10,993	8,558	14,967	15,207	17,239
	21-30	13,010	11,817	8,313	11,592	8,638	14,097	16,115	16,580
	p-value	0.678	0.139	0.306	0.059	0.721	0.959	**0.022**	0.074
Retailer Predicted Profit	**1-10**	4,347	8,532	10,302	10,060	7,303	7,127	9,375	8,443
	11-20	5,795	6,566	8,145	8,201	9,207	5,847	7,664	6,535
	21-30	7,808	4,471	8,517	8,967	9,766	5,622	7,037	5,778
	p-value	**0.005**	0.173	0.240	**0.016**	**0.005**	**0.022**	**0.008**	**0.005**
w	**1-10**	184	156	130	132	154	156	138	145
	11-20	169	166	147	147	138	168	151	161
	21-30	150	193	145	140	134	170	157	168
	p-value	**0.005**	**0.013**	0.283	**0.016**	**0.005**	**0.022**	**0.007**	**0.005**

Pair-1 is interesting. Manufacturer-1 increased the attractiveness of the contract over time by decreasing the wholesale price significantly. Retailer-1 responded by increasing the stock quantity, which caused an increase in only the manufacturer's profit. When we look at the experiment data in detail, we see that this is because of the random demand which turned out to be very low in the last ten periods with a last period demand average of 102 (in comparison to an average of 156 in the first ten periods). Stochasticity in the demand affected the retailer's profit negatively. In Pair-5, for example, the manufacturer decreased the wholesale price significantly over time, which led to higher stock quantity decisions from the retailer's side. The retailer's profit increased significantly consistent with what the retailer's predicted profit suggested. In pair 2, the retailer orders less as a respond to increasing wholesale price. However, the difference is not significant and does not result in significant profit changes for the manufacturer or the retailer.

Next, we analyzed the autocorrelations of the (*w*) decisions for the first ten periods and the last ten periods as summarized in Appendix I to detect whether the manufacturers "stabilized" their decisions towards the end of the interaction. If a subject stabilizes his decisions, one expects autocorrelation in the last 10 periods to be lower relative to the first 10 periods. As shown in Appendix I, we could not find evidence to support this hypothesis. This is similar to the buyback case.

5.2.5.4 Rejected Contracts

Table 5.2.26 presents the rejected contracts in experiment w1a. We observe from Table 5.2.26 that all rejections are made by one single retailer (retailer 3), and the retailer's expected profit is quite good for all of the rejected contracts. We could not come up with an explanation to why he rejected these contracts.

Table 5.2.26 Rejected Contracts with Predicted Results in Experiment w1a

Period of Rejection	**Retailer Number**	**w**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
4	3	180	93	*12,116*	*4,637*
16	3	160	108	*11,924*	*6,649*
17	3	155	112	*11,781*	*7,200*
18	3	160	108	*11,924*	*6,649*
22	3	180	93	*12,116*	*4,637*

5.2.6 Experiment w1b

Experiment w1b has seven manufacturers and seven retailers. Contract rejection is observed in nineteen games.

5.2.6.1 Retailer's Stock Quantity Decision and Firms Profits

Figures 5.2.19(a)-(c) present the mean stock quantity and the firms' profits across seven games over 30 periods. Table 5.2.27 summarizes the results.

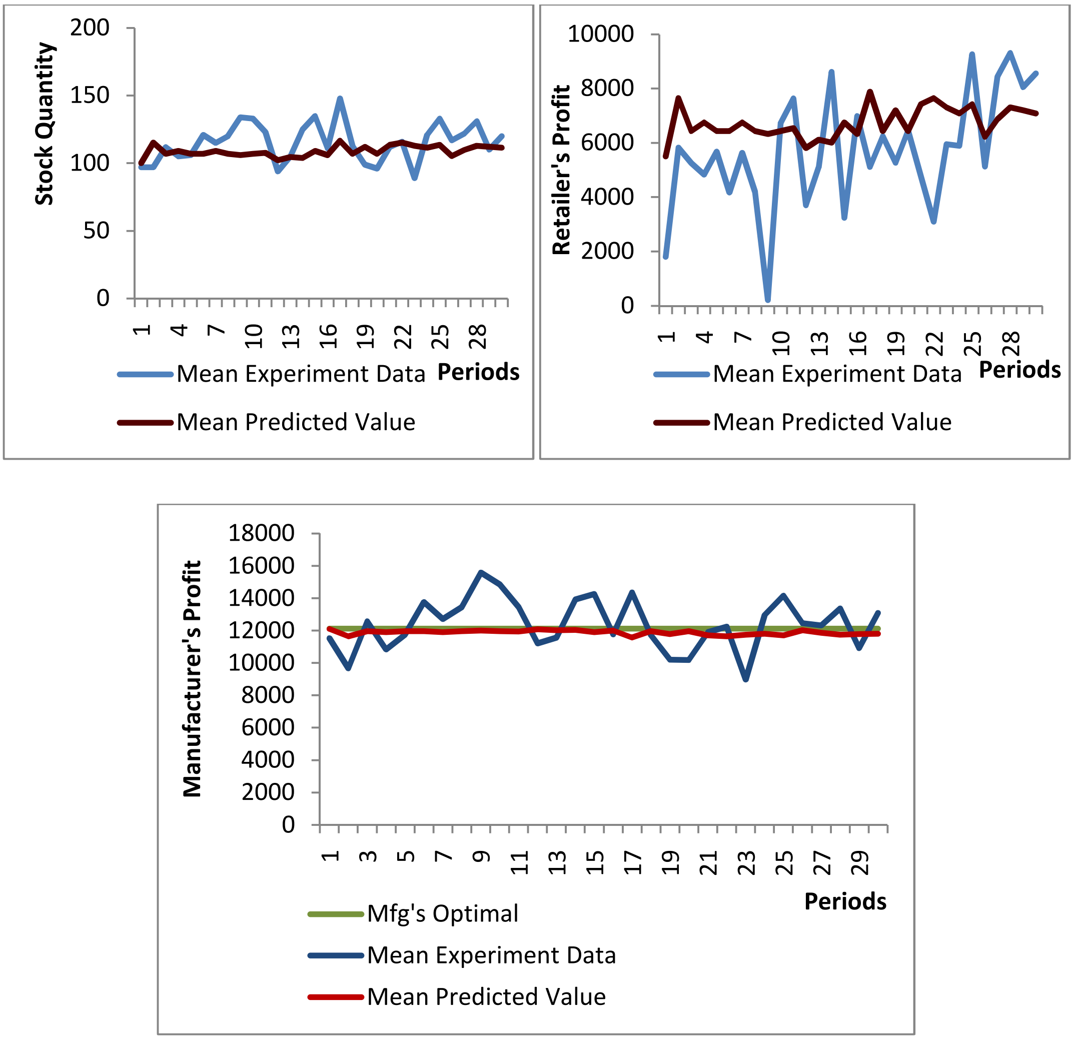


Figure 5.2.19 (a)-(c) Stock Quantity and Profits in Experiment w1b

Table 5.2.27 Stock Quantities and Firms Profits in Experiment w1b

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	115	*109*		5,705	*6,743*		12,390	*11,883*	
Median	116	*108*	**0.018**	5,657	*6,650*	**0.014**	12,388	*11,923*	0.106
St.dev.	14	*4*		2,141	*584*		1,584	*141*	

We observe the overstocking behavior in this experiment, too. The retailers gain significantly lower than predicted, and the manufacturers gain higher than the predicted profit.

5.2.6.2 Manufacturer's Contract Parameter Decisions

Figure 5.2.20 (a)-(c) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.28 summarizes the comparison.

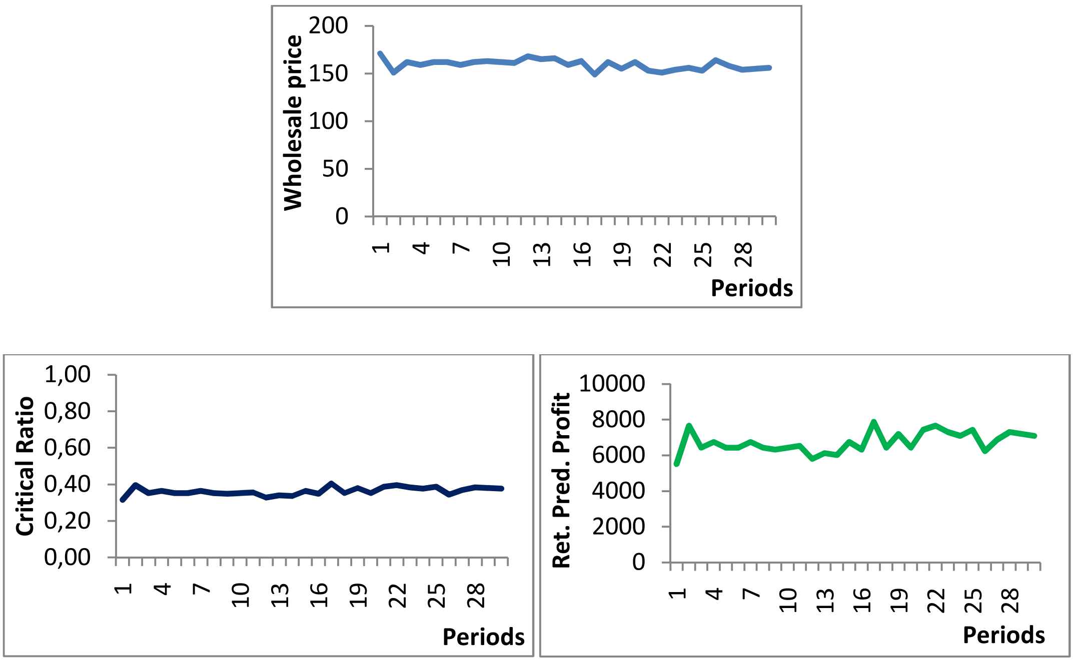


Figure 5.2.20 (a)-(c) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment w1b

Table 5.2.28 Contract Parameters in Experiment w1b

	w (Data)	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	176	0.75	*5,011*
Mean	159	0.36	*6,743*
Median	160	0.36	*6,650*
Stdev	5	0.02	*584*

5.2.6.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.2.29, we test for statistical significance, and we compare the data of the first 10 periods with the last 10 periods.

Table 5.2.29 Mean Values in Three Period Blocks in Experiment w1b

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**CR**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**
Per. 1-10	114	*107*	4,431	*6,518*	12,674	*11,939*	161	0.35
Per. 11-20	115	*108*	5,837	*6,552*	12,260	*11,927*	161	0.36
Per. 21-30	117	*112*	6,846	*7,160*	12,236	*11,785*	155	0.38
p-value	0.575		**0.022**		0.646		**0.015**	**0.015**

We observe that the wholesale price decreases significantly over time and therefore the critical ratio increases at the same level of significance. The manufacturers offer better contracts to the retailers over time. Therefore, the retailers gain significantly higher profits even though the increase in the stock quantity over time is not significant.

5.2.6.4 Rejected Contracts

We observe that almost all of the rejections (15 out of 19) are due to one single player (retailer 3); hence, rejection is not a common retailer strategy. As retailer 3 starts rejecting from the first period, retailer 3 is probably "signaling" to the manufacturer that he is a tough player who will not accept low profits, as she has a fixed partner throughout the experiment. However, all of the rejected contracts would theoretically result in nonnegative profit for the retailer as seen in Table 5.2.30. By rejecting such a contract, the retailer gave up an expected positive profit. Risk aversion may explain this behavior. Although the contract provides positive expected profit, losses are also possible which causes risk for the retailer.

Table 5.2.30 Rejected Contracts with Predicted Results in Experiment w1b

Period of Rejection	**Retailer Number**	**w**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
1	3	175	97	*12,125*	*5,111*
2	3	170	101	*12,096*	*5,605*
3	3	160	108	*11,924*	*6,649*
4	3	160	108	*11,924*	*6,649*
8	3	150	116	*11,600*	*7,770*
9	3	150	116	*11,600*	*7,770*
10	3	150	116	*11,600*	*7,770*
11	3	151	115	*11,639*	*7,655*
12	3	151	115	*11,639*	*7,655*
13	3	151	115	*11,639*	*7,655*
14	3	151	115	*11,639*	*7,655*
15	3	151	115	*11,639*	*7,655*
16	3	150	116	*11,600*	*7,770*
17	3	151	115	*11,639*	*7,655*
18	3	150	116	*11,600*	*7,770*
12	5	168	102	*12,074*	*5,808*
24	5	160	108	*11,924*	*6,649*
25	5	145	120	*11,381*	*8,359*
26	5	150	116	*11,600*	*7,770*

5.2.7 Experiment w1c

Experiment w1c has eight manufacturers and eight retailers. Contract rejection is seen in thirteen games.

5.2.7.1 Retailer’s Stock Quantity Decision and Firms Profits

Figure 5.2.21 (a)-(c) present the mean stock quantity and the firms’ profits across eight games over 30 periods. Table 5.2.31 summarizes the results.

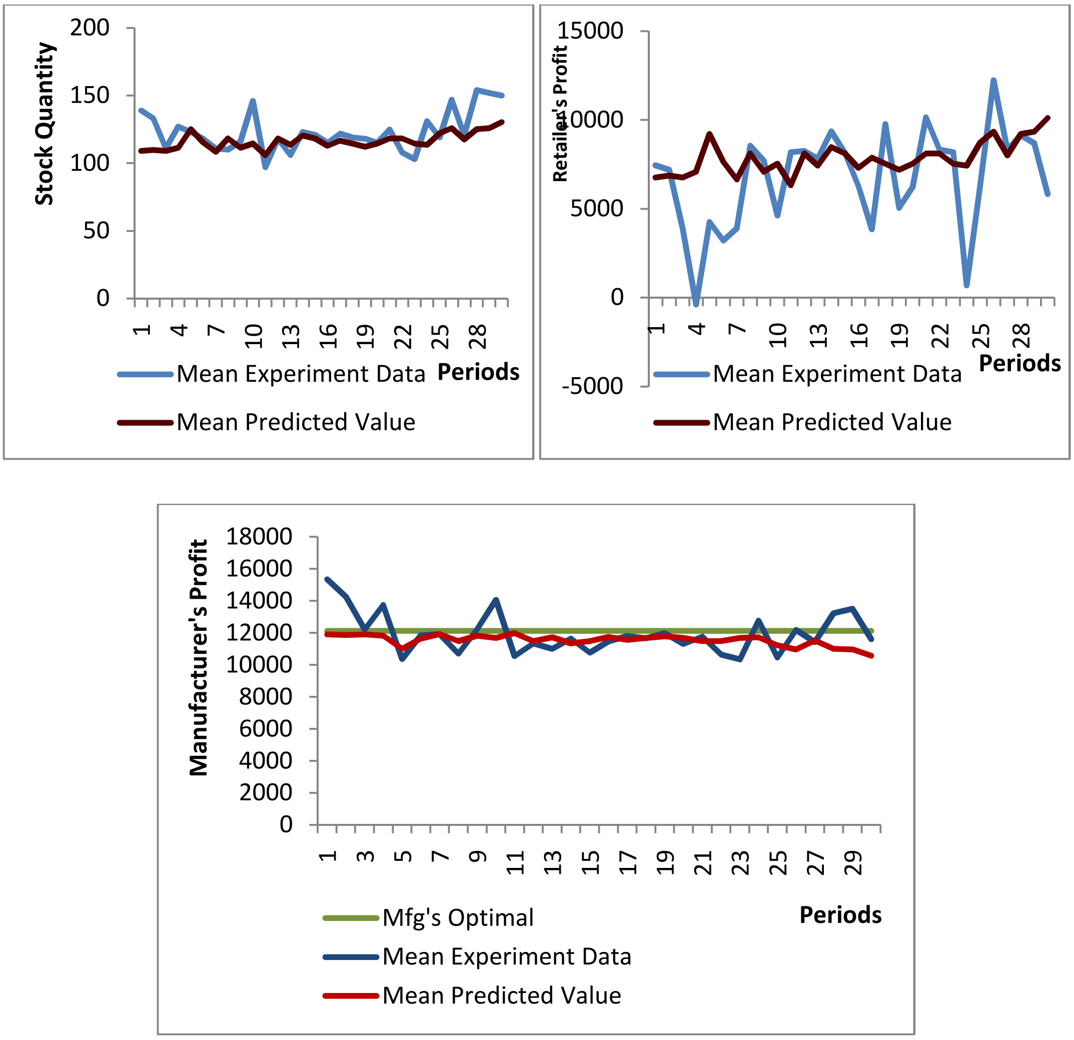


Figure 5.2.21 (a)-(c) Stock Quantity and Firms Profits in Experiment w1c

Table 5.2.31 Stock Quantities and Firms Profits in Experiment w1c

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	123	*116*		6,707	*7,855*		11,935	*11,534*	
Median	120	*115*	**0.012**	7,579	*7,597*	0.106	11,709	*11,658*	0.254
St.dev.	15	*6*		2,794	*921*		1,259	*346*	

Similar to the experiments until now, we observe a significant overstocking behavior of the retailer. The profits are not affected significantly.

5.2.7.2 Manufacturer's Contract Parameter Decisions

Figure 5.2.22 (a)-(c) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.32 summarizes the comparison.

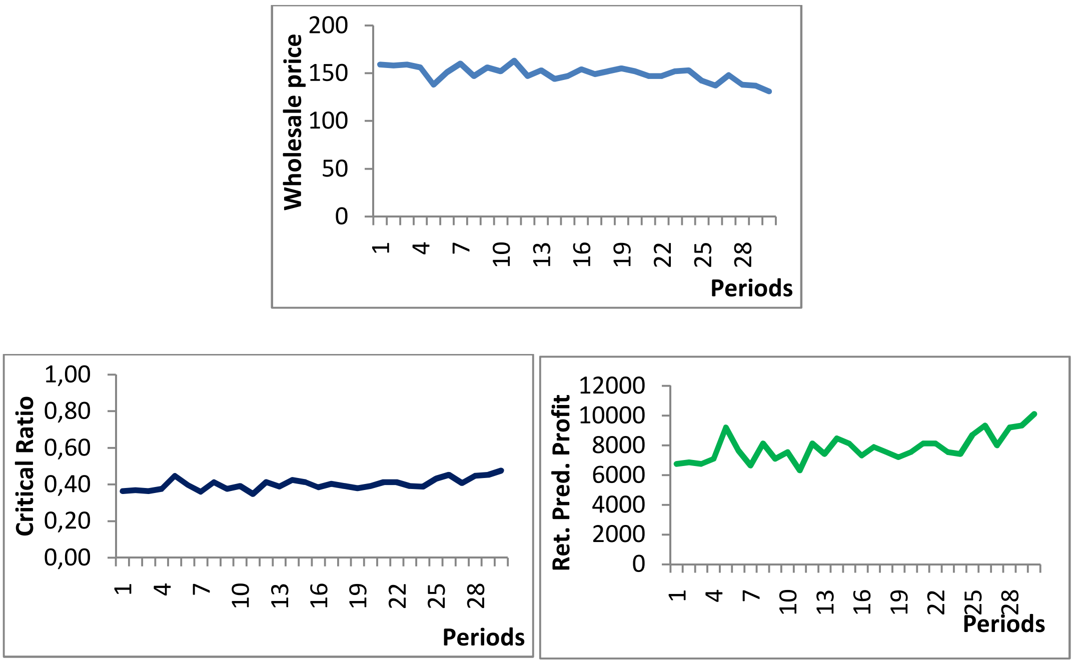


Figure 5.2.22 Wholesale Price, Critical Ratio, and Retailer's Predicted Profit in Experiment w1c

Table 5.2.32 Contract Parameters in Experiment w1c

	w (Data)	**Critical Ratio**	***Retailer's Pred. Profit***
Mfg. Optimal	176	0.75	*5,011*
Mean	149	0.40	*7,855*
Median	152	0.39	*7,597*
Stdev	8	0.03	*921*

5.2.7.3 Changes in Decisions over Time

In Table 5.2.33, we present the subjects' mean decisions and profits in three period blocks and we compare the data of the first 10 periods with the last 10 periods.

Table 5.2.33 Mean Values in Three Period Blocks in Experiment w1c

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**CR**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**
Per. 1-10	123	*113*	5,040	*7,374*	12,665	*11,702*	154	0.39
Per. 11-20	115	*115*	7,290	*7,595*	11,350	*11,643*	152	0.39
Per. 21-30	131	*121*	7,790	*8,594*	11,791	*11,256*	143	0.43
p-value	0.385		**0.005**		0.241		**0.009**	**0.009**

We observe that the wholesale price decreases significantly and the retailer gains significantly higher profits in the last ten periods although the increase in the stock quantity is not significant. This is similar to what we observed in Experiment w1b.

5.2.7.4 Rejected Contracts

All of the rejected contracts would theoretically result in nonnegative profit for the retailer as seen in Table 5.2.34. By rejecting such a contract, the retailer gave up an expected positive profit. But at the same time, she tried to signal her behavior. For instance, retailer 2 signals aggressively that she would not accept the w=190 by using her "veto" option consecutively.

Table 5.2.34 Rejected Contracts with Predicted Results in Experiment w1c

Period of Rejection	**Retailer Number**	**w**	**Q***	***Mfg's Predicted Profit***	***Retailer's Predicted Profit***
2	2	190	86	*11,984*	*3,745*
3	2	190	86	*11,984*	*3,745*
10	2	170	101	*12,096*	*5,605*
18	2	160	108	*11,924*	*6,649*
19	2	175	97	*12,125*	*5,111*
20	2	175	97	*12,125*	*5,111*
1	3	165	105	*12,029*	*6,117*
2	3	150	116	*11,600*	*7,770*
10	3	140	124	*11,124*	*8,967*
21	3	137	126	*10,952*	*9,341*
26	3	130	131	*10,496*	*10,241*
21	5	168	102	*12,074*	*5,808*
29	7	210	70	*11,264*	*2,191*

In the following experiments, namely experiments w2a, w2b, and w2c, the partners are re-determined in each period.

5.2.8 Experiment w2a

Experiment w2a has seven manufacturers and seven retailers. Contract rejection (i.e., setting zero stock quantity) is observed in six games.

5.2.8.1 Retailer's Stock Quantity Decision and Firms Profits

Figures 5.2.23(a)-(c) present the mean stock quantity and the firms' profits across seven games over 30 periods. Table 5.2.35 summarizes the comparison.

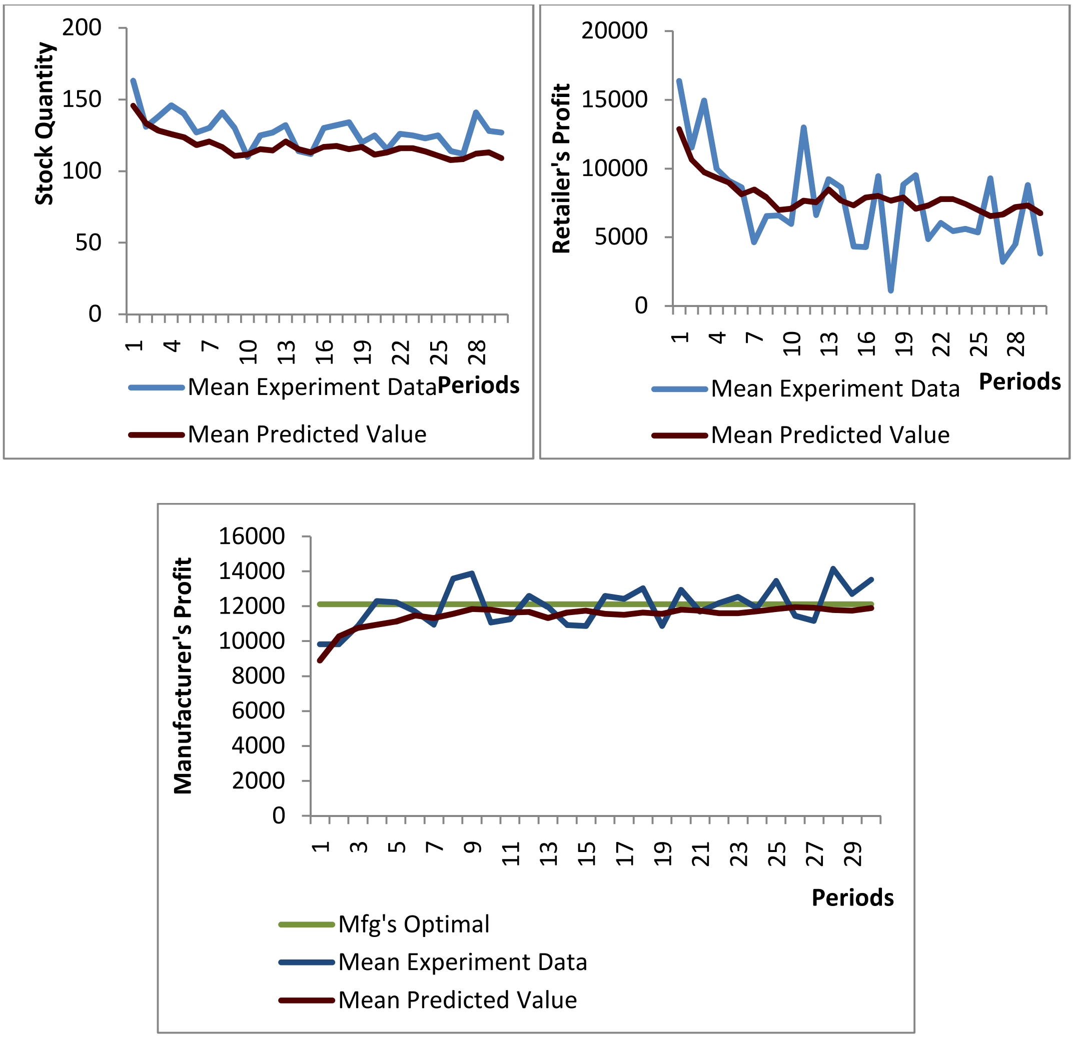


Figure 5.2.23 (a)-(c) Stock Quantity and Firms Profits in Experiment w2a

Table 5.2.35 Stock Quantities and Firms Profits in Experiment w2a

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	128	*117*		7,540	*7,966*		12,017	*11,465*	
Median	127	*115*	**0.000**	6,601	*7,655*	0.219	12,071	*11,639*	0.329
St.dev.	11	*8*		3,453	*1,302*		1,131	*608*	

w2 experiments have pairs which are re-determined every period. However, this structural change does not seem to affect the overstocking behavior of the retailer. As a result, the retailer gains significantly lower profits than predicted. From Figure 5.2.23(b), we observe that the manufacturers offer less attractive contracts over time, leading to reductions in the retailer's profit and increases in their own profits. This is different from what is observed in other experiments. This is due to the behavior of two of the manufacturers, who increase the wholesale price. We will be able to detect the effect of this behavior on the average in the following section.

5.2.8.2 Manufacturer's Contract Parameter Decisions

Figure 5.2.24 (a)-(c) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.36 summarizes the comparison.

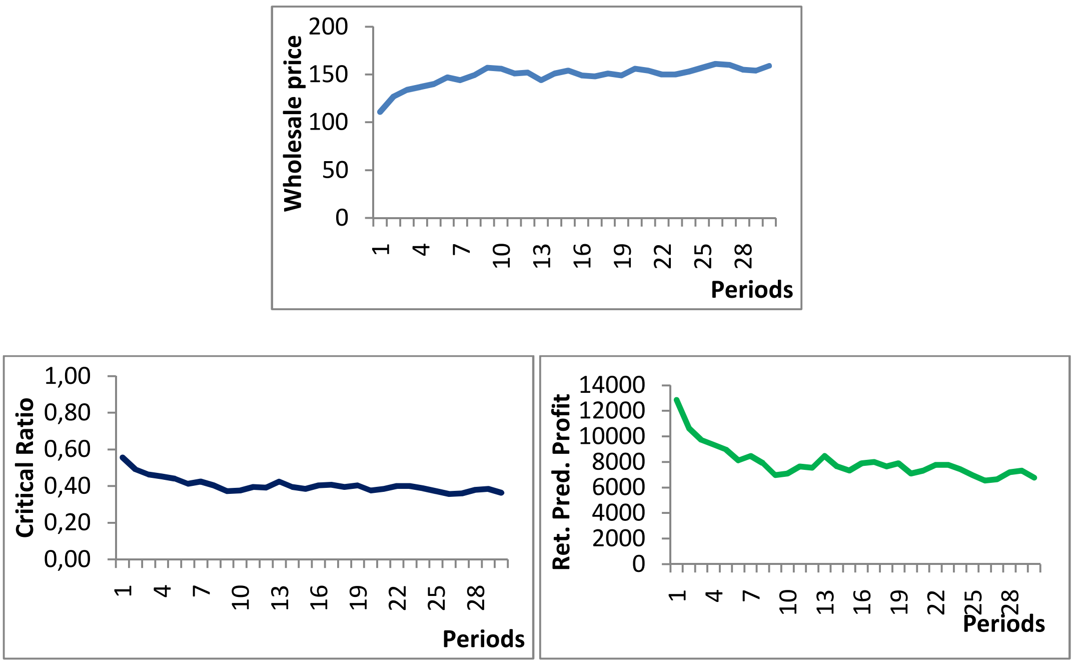


Figure 5.2.24 Wholesale Price, Critical Ratio, and Retailer's Predicted Profit over Time in Experiment w2a

Table 5.2.36 Contract Parameters in Experiment w2a

	w (Data)	Critical Ratio	*Retailer's Pred. Profit*
Mfg. Optimal	176	0.75	*5,011*
Mean	149	0.41	*7,966*
Median	151	0.40	*7,655*
Stdev	10	0.04	*1,302*

We observe that the wholesale price and the critical ratio lie under the manufacturer's optimal as in other experiments.

5.2.8.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.2.37, we present the subjects' mean decisions and profits in three period blocks consisting of periods 1-10, periods 11-20, and periods 21-30. To test for statistical significance, we compare the data of the first 10 periods with the last 10 periods.

Table 5.2.37 Mean Values in Three Period Blocks in Experiment w2a

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**Critical Ratio**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**
Per. 1-10	136	*123*	9,429	*9,009*	11,625	*11,002*	140	0.44
Per. 11-20	125	*116*	7,493	*7,716*	11,945	*11,612*	151	0.40
Per. 21-30	124	*112*	5,699	*7,172*	12,480	*11,780*	155	0.38
p-value	**0.05**		**0.028**		0.074		**0.015**	**0.015**

We observe the manufacturers to increase the wholesale price over time. This causes the retailer's predicted profit to reduce as well. However, the retailer's realized profit reduced even more sharply from the first ten periods to the last ten periods. This is due to the overstocking behavior of the retailers. Manufacturer's profit, on the other hand, increased over time and is higher than its predicted values thanks to the retailer's overstocking behavior.

5.2.8.4 Rejected Contracts

Table 5.2.38 presents the data of the games with rejected contracts. We observe that all of the six rejections are due to one single player (retailer 4); hence, rejection is not a common retailer strategy. This retailer rejected contracts that offered expected profits as high as 6,649.

Table 5.2.38 Rejected Contracts with Predicted Results in Experiment w2a

Period of Rejection	**Retailer Number**	**w**	**Q***	***Mfg.'s Predicted Profit***	***Retailer's Predicted Profit***
3	4	160	108	*11,924*	*6,649*
4	4	200	78	*11,700*	*2,930*
8	4	180	93	*12,116*	*4,637*
11	4	179	94	*12,121*	*4,730*
13	4	168	102	*12,074*	*5,808*
22	4	189	86	*12,004*	*3,831*

5.2.9 Experiment w2b

Experiment w2b has seven manufacturers and seven retailers. This is the only experiment where we do not have any games with contract rejection.

5.2.9.1 Retailer's Stock Quantity Decision and Firms Profits

Figure 5.2.25(a)-(c) presents the mean stock quantity and the firms' profits across seven games over 30 periods. Table 5.2.26 summarizes the comparison.

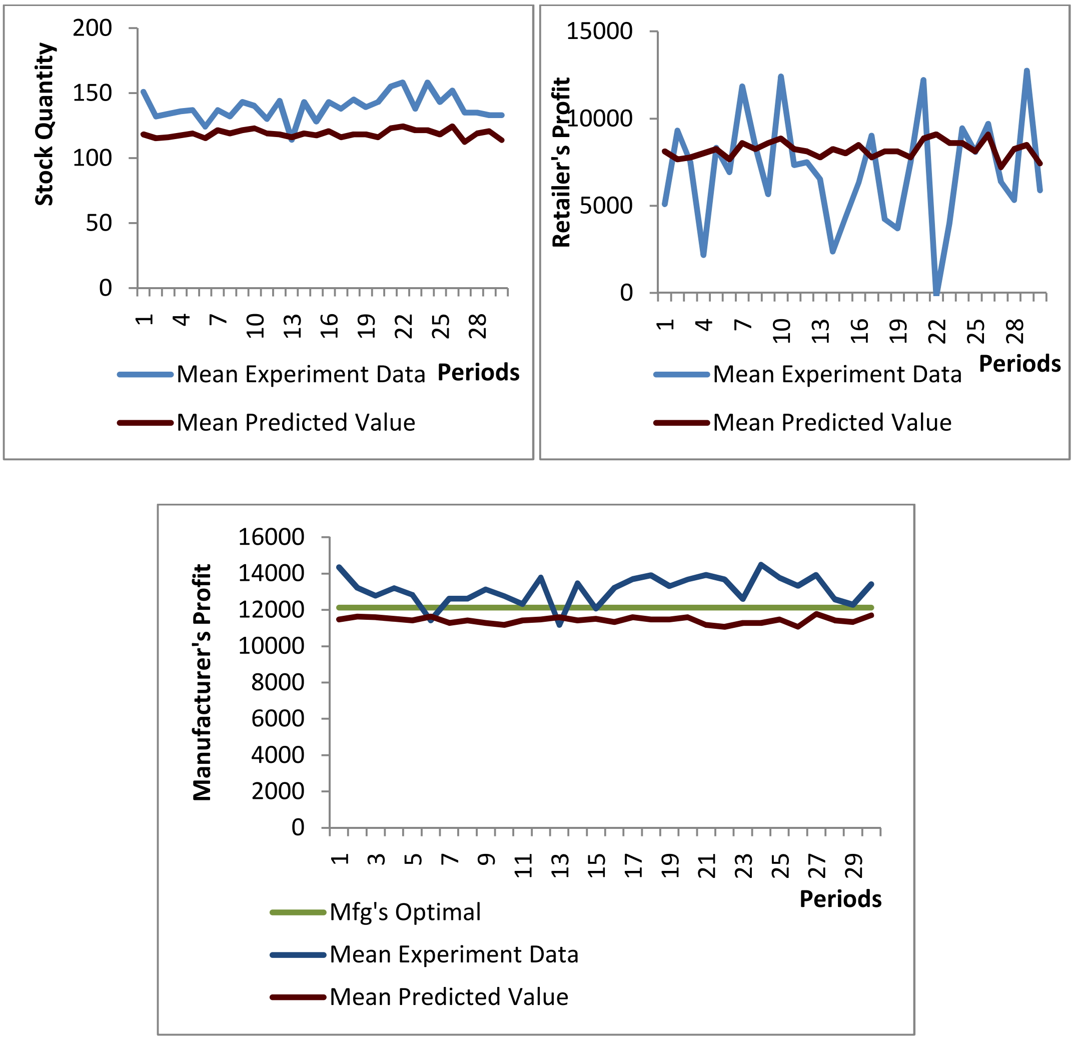


Figure 5.2.25 (a)-(c) Stock Quantity and Firms Profits in Experiment w2b

Table 5.2.39 Stock Quantities and Firms Profits in Experiment w2b

	Stock Quantity			**Retailer's Profit**			**Manufacturer's Profit**		
	Data	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**
Mean	139	*119*		7,003	*8,202*		13,120	*11,433*	
Median	138	*119*	**0.000**	7,128	*8,181*	**0.047**	13,218	*11,451*	**0.000**
St.dev.	10	*3*		3,123	*465*		787	*179*	

We continue to observe overstocking of the retailer in this experiment. The retailers gain significantly lower than predicted, whereas the manufacturers benefit from the deviation of the retailers from the newsvendor quantity.

5.2.9.2 Manufacturer's Contract Parameter Decisions

Figure 11 (a)-(c) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 11 summarizes the comparison.

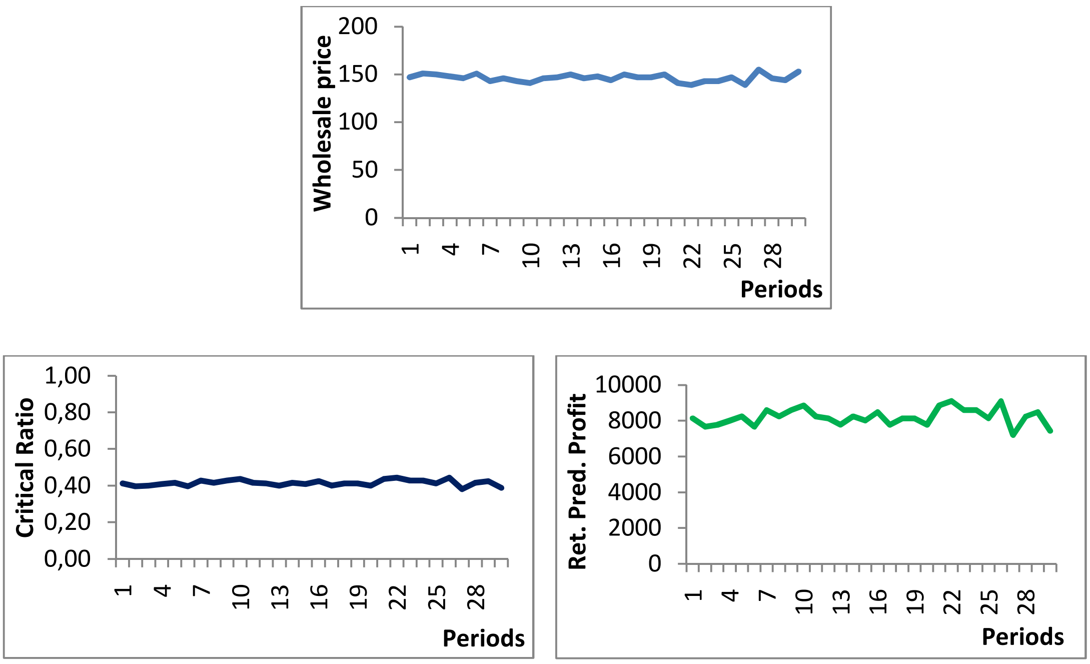


Figure 5.2.26 (a)-(c) Contract Parameters, Critical Ratio and Retailer's Expected Profit in Experiment w2b

Table 5.2.40 Contract Parameters in Experiment w2b

	w (Data)	Critical Ratio	*Retailer's Pred. Profit*
Mfg. Optimal	176	0.75	*5,011*
Mean	146	0.41	*8,202*
Median	147	0.41	*8,181*
Stdev	4	0.02	*465*

5.2.9.3 Changes in Decisions over Time

Next, we present the subjects' mean decisions and profits in three period blocks consisting of periods 1-10, periods 11-20, and periods 21-30. To test for statistical significance, we compare the data of the first 10 periods with the last 10 periods as shown in Table 5.2.41.

Table 5.2.41 Mean Values in Three Period Blocks in Experiment w2b

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**CR**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred***	**Data**	**Data**
Per. 1-10	137	*119*	7,767	*8,173*	12,894	*11,447*	147	0.41
Per. 11-20	137	*118*	5,888	*8,064*	13,063	*11,492*	148	0.41
Per. 21-30	144	*120*	7,354	*8,369*	13,402	*11,361*	145	0.42
p-value	0.169		0.878		0.114		0.590	0.590

Different from other experiments, we cannot detect a significant change between the first ten periods and the last ten periods.

5.2.9.4 Rejected Contracts

There were no games with contract rejection in this experiment.

5.2.10 Experiment w2c

Experiment w2c has seven manufacturers and seven retailers. Contract rejection is seen in six games.

5.2.10.1 Retailer's Stock Quantity Decision and Firms Profits

Figure 5.2.28 (a)-(c) presents the mean stock quantity and the firms' profits across seven games over 30 periods. Table 5.2.42 summarizes the results.

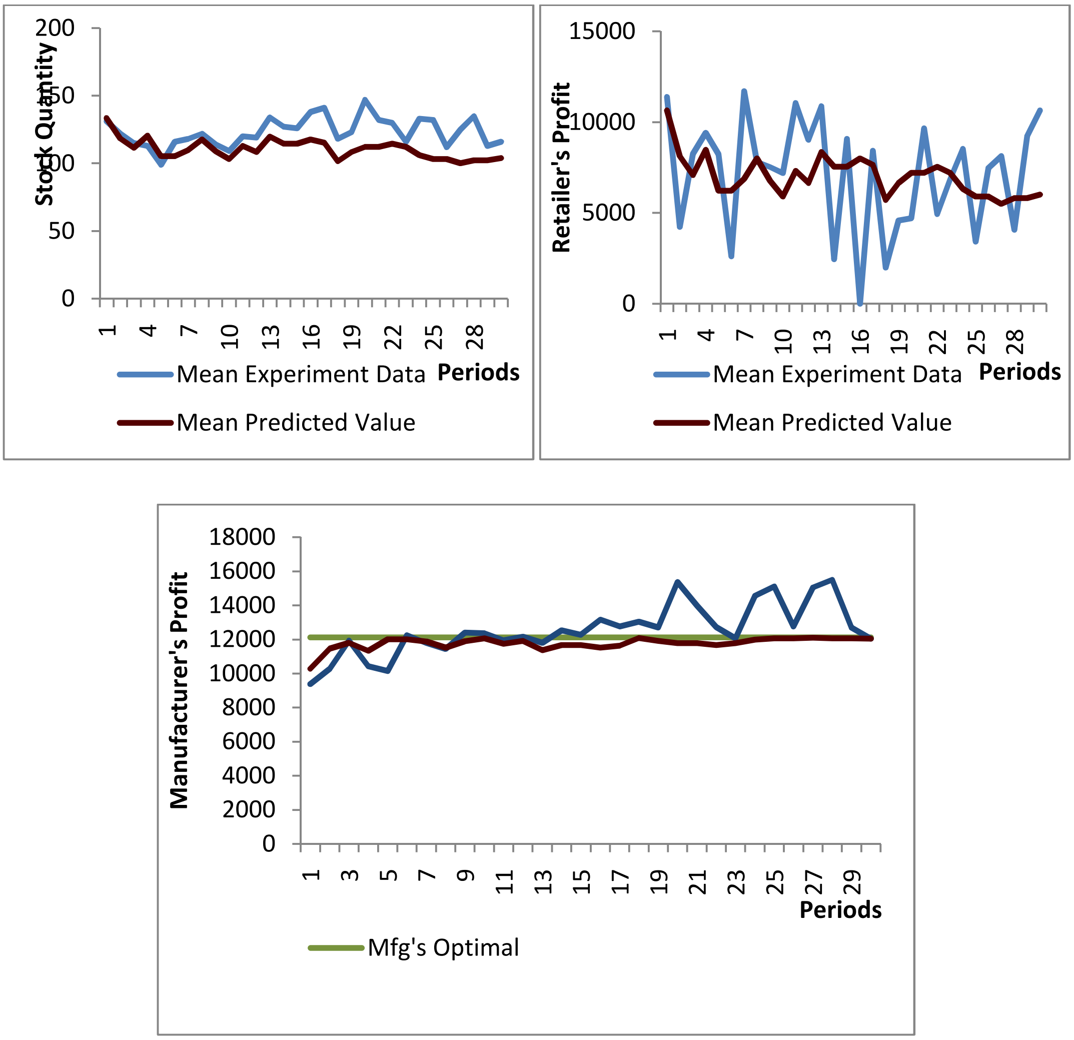


Figure 5.2.27 Stock Quantity and Firms Profits in Experiment w2c

Table 5.2.42 Stock Quantities and Firms Profits in Experiment w2c

	Stock Quantity			**Retailer's Profit**			**Manufacturer's Profit**		
	Data	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**	**Data**	***Pred.***	**p-value**
Mean	123	*111*		7,114	*7,005*		12,559	*11,776*	
Median	122	*111*	**0.000**	7,959	*6,978*	0.719	12,384	*11,842*	0.057
St.dev.	11	*7*		3,110	*1,104*		1,507	*362*	

The retailers, on average, order significantly higher than predicted. Different from other experiments, both the retailer and the manufacturer on average achieved higher profits than predicted. However, this is a result of only one particular player. This retailer gains very high profits in comparison to others (especially during the last periods). Therefore, the data of the retailer's profit becomes higher than the predicted on the average. Due to the same retailer, the difference between median of data and the predicted is also larger than the difference between mean of the data and the predicted. This case is another good example of the effects that one single retailer might cause and affect the experiment average.

5.2.10.2 Manufacturer's Contract Parameter Decisions

Figures 5.2.29 (a)-(c) illustrate the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.2.43 summarizes the results.

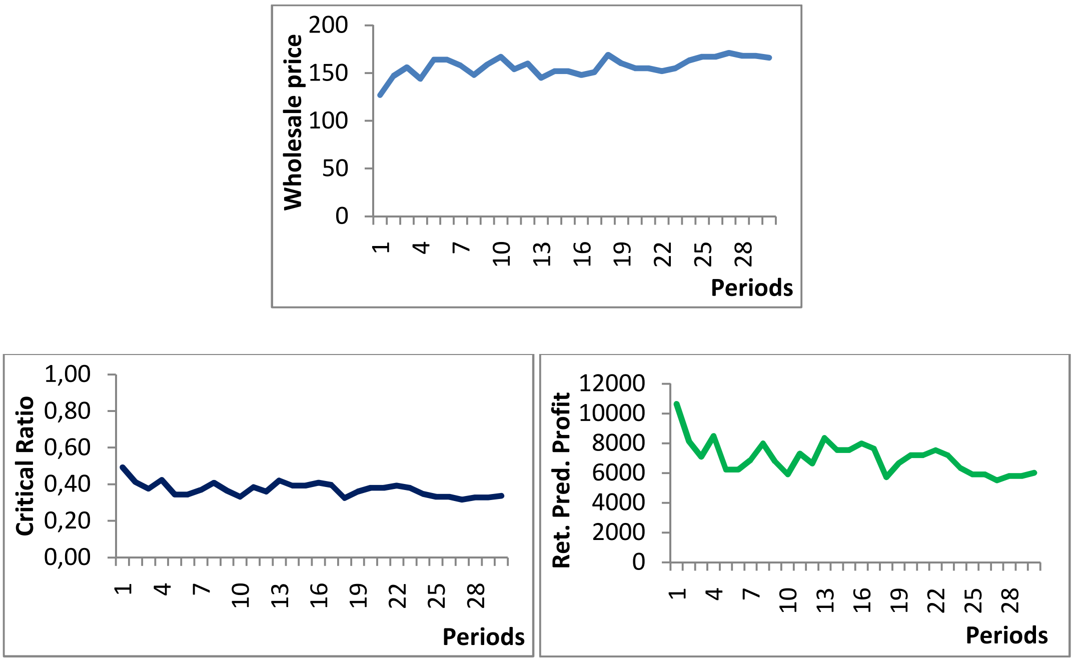


Figure 5.2.28 (a)-(c) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment w2c

Table 5.2.43 Contract Parameters in Experiment w2c

	w (Data)	Critical Ratio	*Retailer's Pred. Profit*
Mfg. Optimal	176	0.75	*5,011*
Mean	157	0.37	*7,005*
Median	157	0.37	*6,978*
Stdev	10	0.04	*1,104*

5.2.10.3 Changes in Decisions over Time

In Table 5.2.44, we present the subjects' mean decisions and profits in three period blocks where we test for statistical significance by comparing the data of the first 10 periods with the last 10 periods.

Table 5.2.44 Mean Values in Three Period Blocks in Experiment w2c

	Stock Quantity		**Retailer Profit**		**Mfg. Profit**		**w**	**Critical Ratio**
	Data	***Pred.***	**Data**	***Pred.***	**Data**	***Pred.***	**Data**	**Data**
Per. 1-10	116	*113*	7,833	*7,431*	11,244	*11,627*	153	0.39
Per. 11-20	129	*113*	6,219	*7,261*	12,778	*11,735*	155	0.38
Per. 21-30	124	*106*	7,291	*6,322*	13,655	*11,965*	163	0.35
p-value	0.126		0.575		**0.009**		**0.021**	**0.021**

The manufacturers increase the wholesale price significantly from the first ten periods to the last ten periods. However, we observe that the retailers do not respond to this increase with a significant decrease in the stock quantity. Instead, they increase their stock quantity. The manufacturer benefits from this behavior and gains significantly higher profits than predicted in the last ten periods. Due to the retailer who gained higher profits in comparison to others, the retailer's profit average in the last ten periods is higher than the predicted value. If that retailer did not participate in the experiment, the retailer's profit on the average would be much lower than the predicted average.

5.2.10.4 Rejected Contracts

Table 5.2.45 summarizes the data for games with rejected contracts. We observe that the rejected contracts usually have low expected profits for the retailer.

Table 5.2.45 Rejected Contracts with Predicted Results in Experiment w2c

Period of Rejection	**Retailer Number**	**w**	**Q***	***Mfg.'s Predicted Profit***	***Retailer's Predicted Profit***
21	1	214	67	*11,047*	*1,917*
24	1	190	86	*11,984*	*3,745*
4	2	229	56	*10,017*	*998*
16	2	231	54	*9,854*	*889*
7	5	249	41	*8,111*	*40*
20	6	250	40	*8,000*	*0*

CHAPTER 6

6. DECISION HEURISTICS

In this chapter, we would like to understand whether the subjects followed "decision heuristics" in making their decisions. We conducted the analysis on the two experiments that we explained in detail in Chapter 5, namely Experiment b1a and Experiment w1a.

6.1. Experiment b1a

6.1.1 Linear Regression

In our study, the periods of a given experiment are independent of each other. That is, the outcome of a period is not affected directly from the decisions or results in a previous period. However, we suspect that a subject's decision in a given period might be affected by the outcome of previous periods due to behavioral reasons. For example, a subject who had a large amount of leftovers on hand at the end of a period might make a more cautious decision in the next period in order not to face the same problem, even though there is no relevance.

Here, we use regression analysis to obtain clues about the underlying behavioral factors that affect subjects' decisions. We conducted the regression analysis using SPSS, with the "backward" variable selection method and with standardized coefficients. The analysis is conducted at two different levels: Experiment-based (where all subjects' data in an experiment is pooled) and subject-based (to investigate subject-based decisions). For all of the variables stated in the regression result tables, the VIF statistic is desired to be less than 10 to avoid multi-collinearity.

6.1.1.1 Regression for the Stock Quantity Decision of the Retailer

Here, we analyze retailer subjects' stock level decisions. First, we control whether there is a significant relationship between the stock level decision and other variables. We control the relationship with multiple and simple regression analysis for the experiment and each subject. Similar to our other analyses, we discarded the data of games where the retailer rejected the contract by setting zero stock quantity. Doing otherwise would cause issues with linear regression.

We conducted regression analysis to regress the response variable, "the retailer's stock level decision at period *t*". The predictor variables and their abbreviations used in the regression are shown in Table 6.1.1.

Table 6.1.1 The Predictor Variables and Their Abbreviations for Retailer's Stock Quantity Decision

Predictor variables	**Abbreviations**
Wholesale price at period t or t-1	w(t) or w(t-1)
Buyback price at period t or t-1	b(t) or b(t-1)
Demand realization at period t-1	D(t-1)
Retailer's profit at period t-1	rp (t-1)
Overage at period t-1	O(t-1)
Underage at period t-1	U(t-1)

In addition to stated predictor variables, we also considered the effect of manufacturer's profit at period *(t-1)*. However, the analysis that included this variable did not result in significant regression equations.

6.1.1.2 Experiment-Based Regression

We tested the null hypothesis that there is no relationship between retailer's stock quantity decision and the variables stated in Table 6.1.1. Results are shown in Table 6.1.2. If the stock quantity decision is expressed by an equation of at least one predictor variable significantly (i.e., if the regression model passed the F test and $p\text{-}value \leq 0.1$), the "response" for that experiment is defined as "yes". "Response variables" show which predictor variables are in the regression model. We also provide R^2, the adjusted R^2 and F-test p-values. "Equation" shows the regression model of the significant analysis, where p-value is less than 0.1. Absolute regression coefficient (absolute beta values) of each predictor variable in an equation indicates the power of that variable in predicting the stock quantity decision.

We observe that 38.3% of the variability in the stock quantity of a retailer can be explained by *w(t), b(t), D(t-1), O(t-1), U(t-1)* on the average. The high absolute beta values indicate that the most effective variables are the wholesale price at period *t* and demand at period *(t-1)*.

Table 6.1.2 Experiment-Based Multiple Linear Regression Results in Experiment b1a for the Retailer

Response	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
yes	w(t) and b(t)	0.319	0.311	**0.000**	Q(t) = 232.722 - 0.775*w(t) + 0.419*b(t)
yes	w(t) and D(t-1)	0.127	0.117	**0.000**	Q(t) = 191.222 - 0.444*w(t) + 0.117*D(t-1)
yes	w(t), b(t), and D(t-1)	0.34	0.328	**0.000**	Q(t) = 220.964 - 0.791*w(t) + 0.416*b(t) + 0.110*D(t-1)
yes	D(t-1), O(t-1)	0.091	0.081	**0.000**	Q(t) = 77.284 + 0.290*D(t-1) + 0.410*O(t-1)
yes	w(t), D(t-1), O(t-1)	0.178	0.164	**0.000**	Q(t) = 152.294 - 0.396*w(t) + 0.278*D(t-1) + 0.340*O(t-1)
yes	w(t), b(t), D(t-1), O(t-1), U(t-1)	0.401	0.383	**0.000**	Q(t) = 166.186 - 0.621*w(t) + 0.329*b(t) + 0.389*D(t-1) + 0.200*O(t-1) - 0.340*U(t-1)
yes	D(t-1), O(t-1), U(t-1)	0.24	0.226	**0.000**	Q(t) = 56.304 + 0.587*D(t-1) + 0.393*O(t-1) - 0.554*U(t-1)
yes	Ret. profit(t-1), w(t) and b(t)	0.337	0.325	**0.000**	Q(t) = 210.541 - 0.671*w(t) + 0.400*b(t) + 0.001*rp(t-1)
yes	Ret. profit(t-1) and D(t-1)	0.163	0.102	**0.000**	Q(t) = 125.145 - 0.083*D(t-1) + 0.002*rp(t-1)

Next, in Table 6.1.3 we provide the results for the simple linear regression studies we conducted for each predictor variable separately.

Table 6.1.3 Experiment-Based Single Linear Regression Results in Experiment b1a for the Retailer

Response	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
yes	wholesale price(t)	0.091	0.091	**0.000**	Q(t) = 195.87 - 0.3711*w(t)
yes	buyback price(t)	0.044	0.043	**0.001**	Q(t) = 116.42 + 0.1518*w(t)
no	demand(t-1)				
yes	wholesale price(t) - buyback price(t)	0.169	0.164	**0.000**	Q(t) = 162.7 - 0.3412*[w(t)-b(t)]
yes	retailer profit (t-1)	0.117	0.110	**0.000**	Q(t) = 118.570 - 0.002*rp(t-1)
no	overage(t-1)				
yes	underage(t-1)	0.054	0.052	**0.010**	Q(t) = 140.86 - 0.2363*U(t-1)

Simple linear regression of Experiment b1a does not result in high adjusted R^2 values. However, we can state that wholesale price of the current period (period *t*) and the difference between the wholesale price and buyback price in the previous period (period *t-1*) are strong variables, as their high absolute beta values suggest.

6.1.1.3 Subject-Based Regression

Here we analyze the stock quantity decision of the retailer in period t by subject-based regression. The results are provided in Table 6.1.4.

Table 6.1.4 Subject-Based Multiple Linear Regression Results in Experiment b1a

Sub.	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
Ret-1	w(t), b(t), D(t-1), O(t-1)	0.799	0.639	**0.054**	Q(t)=19.608-0.353*w(t)+2.076*b(t)+0.119*D(t-1)+0.462*O(t-1)
Ret-2	w(t), b(t), D(t-1), U(t-1)	0.564	0.418	**0.030**	Q(t)=508.519-2.724*w(t)+1.146*b(t)-0.067*D(t-1)+0.329*U(t-1)
Ret-3	w(t), b(t), D(t-1), U(t-1)	0.933	0.865	**0.013**	Q(t)=279.218-2.043*w(t)+1.537*b(t)+0.248*D(t-1)-0.035*U(t-1)
Ret-4	w(t), b(t), O(t-1)	0.852	0.740	**0.039**	Q(t)=330.838-1.946*w(t)+3.704*b(t)+0.090*O(t-1)
Ret-5	w(t), b(t), D(t-1), O(t-1)	0.760	0.654	**0.007**	Q(t)= 811.135-4.542*w(t)+2.430*b(t) + 0.036*D(t-1)-0.028*O(t-1)
Ret-6	w(t), b(t), D(t-1), O(t-1)	0.740	0.625	**0.010**	Q(t)=315.483-1.228*w(t)+1.125*b(t) -1.078*D(t-1)-0.258*O(t-1)

The results are subject-dependent. Yet, not surprisingly, we observe the contract parameters *w(t)* and *b(t)* to affect all retailers' quantity decisions consistently. In addition, demand, overage and underage values in period *(t-1)* are the other variables that explain the differences in the retailers' stock quantity choices. Subject-level regression analysis seems promising: The models are highly significant (i.e., the p-values are less than 0.1) for all retailers and the R^2 values are greater than 0.60 for five out of six retailers.

6.1.1.4 Regression for the Wholesale Price Decision of the Manufacturer

Here we focus on the manufacturers' wholesale price decision. First, we control whether there is a significant relationship between the wholesale price decision and other variables. We control the relationship with multiple and simple regression analysis for each experiment and each subject. The variables that we used for linear regression analysis of the manufacturers' decision are shown in Table 6.1.5 with their abbreviations.

Table 6.1.5 The Predictor Variables and Their Abbreviations for the Manufacturer

Predictor variables	**Abbreviations**
Wholesale price at period t-1	w(t-1)
Buyback price at period t-1	b(t-1)
Demand realization at period t-1	D(t-1)
Retailer's stock quantity at period t-1	Q(t-1)
Manufacturer's profit at period t-1	mp(t-1)

In addition, we tried to explain the buyback price decision of the manufacturer through linear regression. However, we could not find a significant relation with the candidate predictor variables. We also studied whether there is a significant relationship between each manufacturer's *(w,b)* decision at a period with his decisions at previous periods. To this end, we conducted an autocorrelation analysis both for the wholesale price and the buyback price with three lags. This study is presented at Chapter 5, whereas the autocorrelation tables can be found in Appendix H.

6.1.1.5 Experiment-Based Decisions

We tested the null hypothesis that there is no relationship between manufacturer's wholesale price decision with the multiple predictor variables stated in Table 6.1.6. The following analysis is conducted by pooling all experiment b1a data. We regressed 180 decisions of the six manufacturers.

Table 6.1.6 Experiment-Based Multiple Linear Regression Results in Experiment b1a for the Manufacturer's Decision

Response	Predictor variables	R^2	Adj. R^2	p-value	Equation
yes	w(t-1) and b(t-1)	0.778	0.775	**0.000**	w(t) = 24.422 + 0.85 * w(t-1) + 0.037*b(t-1)
yes	Q(t-1) and D(t-1)	0.078	0.067	**0.000**	w(t) = 200.213 - 0.204* Q(t-1) + 0.048*D(t-1)

We observe that 77.5% of the variability in the wholesale price of a manufacturer can be explained by *w(t-1),* and *b(t-1)*. As a second set of candidate predictor variables, we note that *Q(t-1)* and *D(t-1)* can only explain 6.7% of the variability.

Next, in Table 6.1.7.we provide the results for the simple linear regression studies we conducted for each predictor variable separately.

Table 6.1.7 Experiment-Based Simple Linear Regression Results in Experiment b1a for the Manufacturer's Decision

Response	Predictor variables	R^2	Adj. R^2	p-value	Equation
no	w(t-1) - b(t-1)				
yes	Q(t-1)	0.071	0.066	**0.000**	w(t) = 207.025 - 0.207*Q(t-1)
no	D(t-1)				
yes	Mfg. profit(t-1)	0.187	0.182	**0.000**	w(t) = 147.583 + 0.002*mp(t-1)

Even though the adjusted-R^2 values are not high, stock quantity in period *(t-1)* and the manufacturer's own profit in period *(t-1)* yield significant linear regression models.

6.1.1.6 Subject-Based Decisions

Next, we analyze the manufacturer's wholesale price decision by subject. Table 6.1.8 shows the regression results for *w(t)*.

Table 6.1.8 Subject-Based Simple Linear Regression Results in Experiment b1a for the Manufacturer's Decision

Subject	Predictor variables	R^2	Adj. R^2	p-value	Equation
Mfg-1	w(t-1) - b(t-1)	0.125	0.092	**0.065**	w(t)=154.998 + 0.215*[w(t)-b(t)]
Mfg-2	w(t-1), b(t-1), Q(t-1) and D(t-1)	0.765	0.726	**0.000**	w(t)=102.423 - 0.15*Q(t-1) + 0.034*D(t-1) + 0.328*w(t-1) + 0.331*b(t-1)
Mfg-3	w(t-1) and b(t-1)	0.759	0.740	**0.000**	w(t)=3.158+0.935*w(t-1) + 0.077*b(t-1)
Mfg-4	D(t-1), w(t-1) and b(t-1)	0.459	0.391	**0.002**	w(t)=259.552-0.442*w(t-1) + 0.582*b(t-1)+0.043*D(t-1)
Mfg-5	Q(t-1), w(t-1) and b(t-1)	0.648	0.604	**0.000**	w(t)=42.160+0.041*Q(t-1) +0.711*w(t-1)+0.079*b(t-1)
Mfg-6	w(t-1) - b(t-1)	0.164	0.133	**0.029**	w(t)=219.285-0.224 * [w(t-1) - b(t-1)]

The results are subject-dependent. Yet, we observe the contract parameters in the previous period *w(t-1)* and *b(t-1)* to affect all manufacturers' contract parameter decisions consistently. In addition, demand and stock quantity in period *(t-1)* are the other variables that explain the differences in the decisions. Subject-level regression analysis seems promising: The models are highly significant (i.e., the p-values are less than 0.06) for all manufacturers and the R^2 values are greater than 0.60 for three out of six manufacturers.

6.1.2 Orders Related to Previous Waste

Keser and Paleologo (2004) mention two hypotheses from the literature on the possible behaviors of the retailers depending on the leftovers units. According to the *availability hypothesis* (Tverysky and Kahneman, 1974), unsatisfied demand results in an increase in the stock quantity Q in the following period, and overstock results in a decrease in the stock quantity in the following period. In Experiment b1a, we found two retailers that behave as predicted by the availability hypothesis (Binomial test, $p=0.05$). The other hypothesis, *gambler's fallacy* (Camerer and Kunreuther, 1989) makes the opposite prediction. This is because retailer thinks that a specific event is not likely to occur again in the next period. In Experiment b1a, we found only one retailer to behave as predicted by the gambler's fallacy hypothesis (Binomial test, $p=0.05$).

6.1.3 Pull-to-Center Effect

As mentioned in the Literature Review, Schweitzer and Cachon (2000) came up with an important observation called the pull-to-center effect. In their newsvendor experiments, retailers overstocked for products that have high (higher than 50%) profit margin, whereas they understocked products that have low (lower than 50%) profit margin. We conducted retailer and game-based analysis to see if pull-to-center effect exists in our Experiment b1a. Only one out of six retailers in this experiment acted according to pull-to-center effect in the majority of the periods (22 out of 30 periods). Therefore, we cannot find evidence for this effect in Experiment b1a.

6.2. Experiment w1a

6.2.1 Linear Regression

6.2.1.1 Linear Regression for the Stock Quantity Decision of the Retailer

Here, we analyze retailer subjects' stock level decisions. Similar to our other analyses, we discarded the data of games where the retailer rejected the contract by setting zero stock quantity. Doing otherwise would cause issues with linear regression.

We conducted regression analysis to regress the response variable, "the retailer's stock level decision at period t". The predictor variables and their abbreviations used in the regression are as the same as in Table 6.1.1, except the variable *b*, as we do not have buyback price as a contract parameter here.

6.2.1.2 Experiment-Based Regression

We tested the null hypothesis that there is no relationship between retailer's stock quantity decision and the predictor variables in Experiment w1a on the average. *p-values* less than 0.1 as a result of regression analysis means that we can reject the null hypothesis. Results are shown in Table 6.2.1.

We observe that 29.4% of the variability in the stock quantity of a retailer can be explained by *w(t), D(t-1), O(t-1), U(t-1)* on the average. Despite the fact that such R^2 values are not enough for certainty, explaining almost 30% of the variability is also meaningful.

Table 6.2.1 Experiment-Based Multiple Linear Regression Results in Experiment w1a for the Retailer

Response	Predictor variables	R^2	Adj. R^2	p-value	Equation
yes	w(t) and D(t-1)	0.068	0.060	**0.000**	Q(t) = 162.628 + 0.085*D(t-1) - 0.378*w(t)
yes	w(t), D(t-1), O(t-1)	0.155	0.144	**0.000**	Q(t) = 124.977 + 0.274*D(t-1) - 0.36*w(t) + 0.502*O(t-1)
yes	w(t), D(t-1), O(t-1), U(t-1)	0.294	0.281	**0.000**	Q(t) = 103.335 + 0.546*D(t-1) - 0.332*w(t) + 0.470*O(t-1) - 0.483*U(t-1)
yes	D(t-1), O(t-1), U(t-1)	0.251	0.241	**0.000**	Q(t) = 51.354 + 0.552*D(t-1) + 0.483*O(t-1) - 0.496*U(t-1)
no	Ret. profit (t-1) and w(t)				
no	Ret. profit(t-1) and D(t-1)				
yes	w(t) and D(t-1)	0.068	0.060	**0.000**	Q(t) = 162.628 + 0.085*D(t-1) - 0.378*w(t)

Next, in Table 6.2.2 we provide the results for the simple linear regression studies we conducted for each predictor variable separately.

Table 6.2.2 Experiment-Based Simple Linear Regression Results in Experiment w1a for the Retailer

Response	Predictor variables	R^2	Adj. R^2	p-value	Equation
yes	wholesale price(t)	0.054	0.050	**0.000**	Q(t) = 172.856 - 0.37*w(t)
yes	demand(t-1)	0.012	0.070	**0.100**	Q(t) = 104.947 - 0.078*D(t-1)
no	Ret. profit(t-1)				
yes	overage(t-1)	0.023	0.019	**0.020**	Q(t) = 111.899 + 0.184*O(t-1)
yes	underage(t-1)	0.038	0.034	**0.030**	Q(t) = 122.224 - 0.172*U(t-1)

Simple linear regression results in even lower adjusted-R^2 values. We can not find any supportive ideas to explain the stock quantity decision. The predictor variable with the highest adj.-R^2 is the wholesale price in the previous period with 5.4%.

6.2.1.3 Subject-Based Regression

Next, we analyze the stock quantity decision of the retailer in period t by subject-based regression. The results are provided in Table 6.2.3.

Table 6.2.3 Subject-Based Multiple Linear Regression Results in Experiment w1a

Sub.	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
Ret. 1	w(t), and D(t-1)	0.330	0.214	**0.029**	Q(t)=184.644-0.743*w(t)+0.315*D(t-1)
Ret. 2	w(t), D(t-1), O(t-1)	0.799	0.795	**0.002**	Q(t)=254.832-0.141*D(t-1)-0.037*O(t-1)-0.872*w(t)
Ret. 3	w(t), D(t-1), O(t-1)	0.632	0.598	**0.031**	Q(t)=237.001-0.014*D(t-1)-0.034*O(t-1)-0.898*w(t)
Ret. 4	w(t), D(t-1), O(t-1)	0.822	0.819	**0.000**	Q(t)=487.595+0.619*D(t-1)+0.740*O(t-1)-2.795*w(t)
Ret. 5	w(t), D(t-1), U(t-1)	0.987	0.982	**0.000**	Q(t)=252.690-0.009*D(t-1)-0.903*w(t)-0.004*U(t)
Ret. 6	Retailer profit(t-1) and D(t-1)	0.222	0.177	**0.030**	Q(t)=78.235+0.003*rp(t-1)+0.126*D(t-1)
Ret. 7	w(t), D(t-1), O(t-1)	0.718	0.694	**0.012**	Q(t)=247.170-0.090*D(t-1)+0.559*O(t-1)-1.384*w(t)
Ret. 8	w(t), D(t-1), U(t-1)	0.827	0.816	**0.000**	Q(t)=147.406+0.116*D(t-1)-0.475*w(t)+ 0.171*U(t-1)

Similar to Experiment b1a, the results are subject-dependent. However, we observe that the the realized demand in the previous period, *D(t-1),* affects all retailers' quantity decisions consistently. In addition, wholesale price, demand, overage and underage values in period *(t-1)* are the other variables that explain the differences in the retailers' stock quantity choices. The models in the subject-level regression are highly significant (i.e., the p-values are less than 0.1) for all retailers.

6.2.1.4 Regression for the Wholesale Price Decision of the Manufacturer

Here we focus on the manufacturers' wholesale price decision. We control the relationship with multiple and simple regression analysis for each subject. The variables that we used for linear regression analysis of the manufacturers' decision are the same as the ones shown in Table 6.1.5 except we do not have buyback price here.

We also studied whether there is a significant relationship between each manufacturer's *(w)* decision at a period with his decisions at previous periods. To this end, we conducted an autocorrelation analysis both for the wholesale price with three lags. This study is presented at Chapter 5, whereas the autocorrelation tables can be found in Appendix I.

6.2.1.5 Experiment-Based Decisions

When we conduct multiple linear regression to predict *w(t)*, we cannot find significant regression outcomes. Therefore, we cannot explain the variability in the wholesale price by multiple linear regression. The multiple predictor variables that we regressed can be seen in Table 6.2.4.

Table 6.2.4 Experiment-Based Multiple Linear Regression Results in Experiment w1a for the Manufacturer's Decision

Response	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
no	w(t-1) and D(t-1)				
no	D(t-1) and Q(t-1)				

If we use simple linear regression, we can only find significant outcomes with the manufacturer's profit, where we are able to explain only 3.6% of the variability with very low beta coefficient as seen in Table 6.2.5.

Table 6.2.5 Experiment-Based Simple Linear Regression Results in Experiment w1a for the Manufacturer's Decision

Response	**Predictor variables**	**R^2**	**Adj. R^2**	**p-value**	**Equation**
no	Q(t-1)				
no	D(t-1)				
yes	Manufacturer profit (t-1)	0.036	0.032	**0.004**	w(t) = 142.825 + 0,01 * Manuf.profit(t-1)
no	Q(t-1)				

We conclude that linear regression does not help us to explain the wholesale price averages in Experiment w1a.

6.2.1.6 Subject-Based Decisions

Despite the fact that we could not find any significant predictor variables on the average, we can explain the variability of the wholesale price for four out of eight manufacturers as in Table 6.2.6. For the ones that we detect significant predictor variables, we observe that the wholesale price in the previous period always exists as one of the predictors.

On the whole, linear regression is not considered as a strong tool for explaining the decision heuristics in Experiment w1a.

Table 6.2.6 Subject-Based Simple Linear Regression Results in Experiment w1a for the Manufacturer's Decision

Subject	Predictor variables	R^2	Adj. R^2	p-value	Equation
Mfg-1	No response from the variables				
Mfg-2	No response from the variables				
Mfg-3	w(t-1) and D(t-1)	0.794	0.778	**0.000**	Q(t)=73.999+0.867*w(t-1)-1.867*D(t-1)
Mfg-4	w(t-1) and D(t-1)	0.260	0.203	**0.020**	Q(t)=86.446+0.555*w(t-1)-0.162*D(t-1)
Mfg-5	w(t-1) and D(t-1)	0.651	0.624	**0.000**	Q(t)=58.297+0.795w(t-1)-0.425*D(t-1)
Mfg-6	No response from the variables				
Mfg-7	Mfg. prof. (t-1) and w(t-1)	0.195	0.165	**0.017**	Q(t)=117.342+0.003*mp(t-1) +0.076*w(t-1)
Mfg-8	No response from the variables				

6.2.2 Orders Related to Wholesale Prices

Parallel to Keser and Paleologo (2004), we try to support our regression analysis in the wholesale price contract by analyzing the retailers' responses to wholesale price changes. For each of the retailers, we examine whether she reacted to an increase (or decrease) in w from $t-1$ to t, with a decrease (or increase) in the stock quantity Q. Binomial test (significance 5%) shows that only one retailer out of eight reacted to an increase (or decrease) in w from $t-1$ to t, with a decrease (or increase) in Q.

6.2.3 Orders Related to Previous Waste

In Experiment w1a, we found no retailers that behave as predicted by the *availability hypothesis*, where unsatisfied demand results in an increase in the stock quantity Q in the following period, and overstock results in a decrease in the stock quantity in the following period (Binomial test, $p=0.05$). In Experiment w1a, we found only one retailer to behave as predicted by the *gambler's fallacy hypothesis*, which implies the opposite of availability hypothesis (Binomial test, $p=0.05$).

6.2.4 Pull-to-Center Effect

We conducted retailer and game-based analysis to see if pull-to-center effect exists in our Experiment w1a. Three out of eight retailers in this experiment acted according to pull-to-center effect in the majority of the periods (Ret-3: 27, Ret-4:15, Ret-5:28 out of 30 periods).

CHAPTER 7

7. CONCLUSION AND FUTURE RESEARCH

We conducted experiments with human decision makers on a manufacturer-retailer supply chain where the retailer faces a newsvendor problem. Contrary to the theoretical predictions, we find the efficiency of the wholesale price contract and buyback contract to be close to each other. The buyback contract failed to improve supply chain profits, but only increased the manufacturer's profit at the expense of the retailer's profit. After Keser and Paleologo (2004), we are the first to conduct supply chain contracting experiments (involving newsvendor retailers) where both firms are represented by humans. We extend Keser and Paleologo (2004) to buyback contracts and we also study the effect of relationship length.

In the buyback contract experiments, we observe the manufacturers to offer contracts that provide a reasonable expected profit to the retailer. This is quite different from their theoretically optimal buyback contract where the retailer is allowed to make only a negligible profit. The ultimatum structure (see Camerer 2003) of the relationship and "fairness" concerns of subjects (see Bolton and Ockenfels 2000) provides a possible explanation. The manufacturer may be concerned about the well being of the retailer, and may not find it "fair" to offer a contract with low expected profit level. Alternatively, the manufacturer may not care about fairness, but he thinks that the retailer cares about fairness. After all, the retailer has the vetoing power: She can reject a contract that she thinks is "unfair", even when this is not the rational choice. The retailers did not resort to this weapon often in our experiments. However the fear of contract rejection is likely to have affected manufacturers' contract parameter decisions.

Bounded rationality of the manufacturers may also be effective. Making the necessary calculations with two contract parameters is not an easy task, despite the aid of the decision support tool. Hence, it is possible that the manufacturers simply could not calculate their optimal contract parameters to begin with. Risk aversion of the manufacturer can also be a factor. The manufacturer may be unwilling to set a high buyback price because this would imply higher risk due to stochastic demand. By setting low wholesale and buyback prices, the manufacturers escaped from assuming sufficient inventory risk. Note that consistent with the literature, we considered take-it-or-leave-it contracts. The results may definitely change if one allows the subjects to negotiate (see Haruvy, Katok and Pavlov 2011). This offers an interesting extension to our work.

While buyback contract performed poorly, the wholesale price proved to be more efficient than the theoretical prediction. If fairness was a factor affecting our subjects, this observation is in line with the theoretical findings of Cui et al. (2007) who show that a simple wholesale price contract can coordinate the channel when the firms care about fairness. The manufacturers offered lower wholesale prices than predicted, leading to higher stock quantities by retailers which benefited both the retailer and the manufacturer (slightly).

For both contract types, we observe the retailers to overstock relative to the predicted newsvendor quantity. This is in line with Cachon and Schweitzer (2000)'s low/high pattern observation but contradicts Keser and Paleologo (2004). Because the theoretical prediction is for the newsvendor to "understock" relative to supply chain optimum, this overstocking bias actually helps improve supply chain profit. The retailer's profit goes down a little, yet the manufacturer's profit improves considerably. Hence, not all overstocking is detrimental.

We expected to observe better performance in the long-run relationship experiments where the same manufacturer-retailer pair interacted for 30 periods, than in the short-run relationship experiments. However, we observed just the opposite: Total profits are higher in the short run relationship games when the pairs are re-determined each period. Destructive "gaming" between the subjects in the long-run games may offer an explanation. This finding has implications for operations management practice, where long-run relationships between firms are favored over short-run ones.

Another widespread observation is the lack of significant learning (similar to Schweitzer and Cachon 2000). One expects the subjects to learn about the interaction, and improve profits over time. Learning is weak even in the long-run relationship experiments where the same pair interacted for 30 periods. As Schweitzer and Cachon comment, if learning is absent in our experimental setting, it is even less likely to be observed in practice where feedback (in terms of business success) is slower and more ambiguous. One can extend our work by focusing on the feedback and learning mechanisms. Our work can also be extended by conducting experiments with a higher number of periods. Although long experiments might result in demotivation of the subjects, a larger data pool might lead to more significant results in terms of learning.

Human subjects' decisions in experiments exhibit wide variation. Similar to other works in literature (see the discussions in Bolton and Katok 2008, and Becker-Peth, Katok and Thonemann 2009), a significant portion of our results are based on "average decisions". While such results are helpful in outlining the "expected behavior", one should not underestimate the variability around these expected values when predicting human behavior.

In spite of all developments in information technology and information systems, it is still the human managers that make decisions in firms. As such, understanding the human biases related to supply chain contracts would be a rewarding endeavor. Experiments with humans allow firms and researchers to test contracts in a laboratory environment before making costly tests in the field. In addition, they can also be used as training tools.

From research point of view, experiments with humans not only offer a way to test the predictive power of the analytical models but also point to the directions to improve these models. By doing so, they introduce the "human dimension" into analytical modeling. Experiments are particularly helpful in the field of supply chain contracting because firms hardly ever share contractual information with outsiders. Our study identified a number of biases affecting the performance of wholesale price and buyback contracts in the presence of human-to-human interaction. Identifying such deviation from theory allows one to modify the contracts to account for, or to take advantage of deviations. Future studies are needed to analyze these biases in detail and to incorporate them into analytical models.

We used discrete uniform distribution in our experimental setting to replicate the setting of Keser and Paleologo (2004). Uniform distribution is popular in literature (Katok and Wu 2009, Schweitzer and Cachon, 2000, Bostian et al, 2008, Bolton and Katok, 2008). We believe the simplicity of uniform distribution might explain this popularity. It can be easily understood by the participants. However, one can also use other distributions in experiments.

In our experiments, the parameters are set by the participants afresh in each game. Alternatively, one can study a setting where the subjects' decisions cannot be changed for a number of periods (Bolton and Katok 2008 offers an example). For example, the manufacturer may be allowed to change the contract parameters every five periods, but not in between. Such a scenario may reflect business cases where contract parameters are not frequently changed.

Our subject pool comprised undergraduate students at Sabancı University. Using students as experimental subjects is common practice in experimental economics and researchers have found no significant difference between students' and professionals' performance in experiments (see, for example Ball and Cech 1996, and Katok, Thomas and Davis 2008, and Bolton, Ockenfals, Thonemann 2008). Yet, the "external validity" of our results is always an issue, as it is with all experimental studies. To this end, we plan to repeat our study using Executive MBA students in the future.

Standard method of motivation in experiments is monetary payment. We chose to motivate students differently, through a bonus grade. The bonus grade was highly prized by students, and as indicated in the exit surveys, provided strong motivation.

This work merely scratches the surface of potential experiments on supply chain contracting. One immediate extension is the study of other contract types such as the revenue sharing, quantity discounts and rebate contracts. Another extension is to conduct a deeper study on the decision heuristics of subjects, and on the factors affecting their decisions. In this thesis, we report the results of some work in this direction. This preliminary work; however, fails to find evidence for the use of decision heuristics. Finally, one can also develop detailed models regarding the learning process (using an Experience Weighted Attraction (EWA) learning model) and bounded rationality (using a Quantal Response Equilibrium (QRE) model).

BIBLIOGRAPHY

Arrow K. J., T. Harris, J. Marschak. 1951. Optimal inventory policy. *Econometrica* **19**(3) 250-272.

Ball, S., P. Cech. 1996. Subject pool choice and treatment effects in economic laboratory research. *Research in Experimental Economics* **6** 239–292.

Becker-Peth, M., E. Katok, U. W. Thonemann. 2009. Designing contracts for irrational but predictable newsvendors. *Management Science,* forthcoming.

Bendoly, E., K. Donohue, K. L. Schultz. 2006. Behavior in operations management: Assessing recent findings and revisiting old assumptions. *Journal of Operations Management* **24** 737-752.

Benzion, U., Y. Cohen, R. Peled, T. Shavit. 2008. Decision-making and the newsvendor problem: an experimental study. Journal of the Operational Research Society **59** 1281-1287.

Bolton, G. E., E. Katok. 2008. Learning-by-doing in the newsvendor problem: A laboratory investigation of the role of experience and feedback. *Manufacturing & Service Operations Management* **10**(3) 519–538.

Bolton, G. E., A. Ockenfels. 2000. ERC: a theory of equity, reciprocity and competition.*The American Economic Review* **90**(1) 166-193.

Bolton, G. E., A. Ockenfels, Thonemann U. 2008. Managers and students as newsvendors: How out-of-task experience matters. Working paper.

Bostian, AJ A., C. A. Holt, A. M. Smith. 2008. Newsvendor "Pull-to-center" effect: Adaptive learning in a laboratory experiment. *Manufacturing & Service Operations Management* **10**(4) 590-608.

Cachon, G. 2003. Supply chain coordination with contracts. A.G. de Kok, S.C. Graves, eds. Chapter 6 in *Handbooks in Operations Research and Management Science, Vol. 11* Elsevier, Amsterdam.

Cachon, G., M. A. Lariviere. 2005. Supply chain coordination with revenue-sharing contracts: Strengths and limitations. *Management Science* **51**(1) 31-44.

Camerer, C. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction.* Princeton University Press.

Camerer, C., H. Kunreuther. 1989. Decision processes for low probability events: policy implications. *Journal of Policy Analysis and Management* **8**(4) 565-592.

Chopra, S., P. Meindl. 2007. *Supply Chain Management: Strategy, Planning and Operation* (Third edition). Pearson Prentice Hall.

Corbett, C., C. J. Fransoo. 2007. Entrepreneurs and newsvendors: Do small businesses follow the newsvendor logic when making inventory decisions? Working paper.

Croson, D. C., R. Croson, Y. Ren. 2008. How to manage an overconfident newsvendor? Working Paper, University of Texas at Dallas.

Croson, R., K. Donohue. 2003. Impact of point of sale (POS) data sharing on supply chainmanagement: An experimental study. *Production and Operations Management* **12**(1) 1-11.

Croson, R., K. Donohue. 2005. Upstream versus downstream information and its impact on the bullwhip effect. *System Dynamics Review* **21**(3) 249-260.

Croson, R., K. Donohue. 2006. Behavioral causes of the bullwhip effect and the observed value of inventory information. *Management Science* **52**(3) 323-336.

Cui, T. H., J. S. Raju, Z. J. Zhang. 2007. Fairness and channel coordination. *Management Science* **53**(8) 1303–1314.

Donohue, K. L. 2000. Efficient supply contracts for fashion goods with forecast updating and two production modes. *Management Science* **46**(11) 1397-1411.

Eeckhoudt L., C. Gollier, H. Schlesinger. 1991. Increases in risk and deductible insurance. *Journal of Economic Theory* **55** 435-440.

Eeckhoudt, L., C. Gollier, H. Schlesinger. 1995. The risk-averse (and prudent) newsboy. *Management Science* **41**(5) 786-794.

Emmons, H., Gilbert, S.M., 1998. Returns policies in pricing and inventory decisions for catalogue goods. *Management Science* **44**(2) 276-283.

Feng, T., L. R. Keller, X. Zheng. 2010. Decision making in the newsvendor problem: A cross-national laboratory study. *Omega, International Journal of Management Science* **39**(1) 41-50.

Fisher M., A. Raman. 1996. Reducing the cost of demand uncertainty through accurate response to early sales. *Special Issue on New Directions in Operations Management* **44**(1) 87-99.

Gavirneni, S., A. M. Isen. 2010. Anatomy of a newsvendor decision: Observations from a verbal protocol analysis. *Production and Operations Management* **19**(4) 453–462.

Gino, F., G. Pisano. 2008. Toward a theory of behavioral operations. *Manufacturing & Service Operations Management* **10**(4) 676-691.

Haruvy, E., E. Katok, V. Pavlov. 2011. Can coordinating contracts improve channel efficiency? Working paper.

Ho, T., J. Zhang. 2008. Designing pricing contracts for boundedly rational customers: Does the framing of the fixed fee matter? *Management Science* **54**(4) 686-700.

Kagel, J.H., A. E. Roth. 1995. Introduction to experimental economics J. H. Kagel and A. E. Roth eds. Chapter 1 in *The Handbook of Experimental Economics.* Princeton.

Kahneman, D., A. Tversky. 1974. Judgment under uncertainty: Heuristics and biases. *Science* **185** 1124-1131.

Kahneman, D., A. Tversky. 1984. Choices, values, and frames. *American Psychologist* **39**(4) 341-350.

Kahneman, D., P. Slovic, A. Tversky. 1982. *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge University Press, Cambridge.

Kandel, E., 1996. The right to return. *Journal of Law and Economics* **39** 329-356.

Katok, E., D. Thomas, A. Davis. 2008. Inventory service level agreements as coordination mechanisms: the effect of review periods. *Manufacturing & Service Operations Management* **10**(4) 609-624.

Katok, E., D. Y. Wu. 2009. Contracting in supply chains: A laboratory investigation. *Management Science* **55**(12) 1953-1968.

Kaya, M., Ö. Özer. 2011. Risk and information sharing in supply chains through pricing contracts. Ö. Özer and R. Phillips eds. to appear in *Handbook of Pricing Management*. Oxford University Press.

Keser, C., G. A. Paleologo. 2004. Experimental investigation of supplier-retailer contracts: the wholesale price contract. *Scientific Series* C*irano* **57**.

Khouja, M. 1999. The single period (news-vendor) inventory problem: A literature review and suggestions for future research. *Omega* **27** 537-55.

Lariviere, M. A. 1999. Supply chain contracting and coordination with stochastic demand. S. Tayur, M. Magazine, & R. Ganeshan, eds in *Quantitative Models of Supply Chain Management*. Boston: Kluwer Academic Publishers, 233-268.

Lee, H. L., V. Padmanabhan, S. Whang. 1997. Information distortion in a supply chain: The bullwhip effect. *Management Science* **43**(4) 546-558.

Lim, N., T. Ho. 2007. Designing price contracts for boundedly rational customers: does the number of blocks matter? *Marketing Science* **26**(3), 312–326.

Loch, C. H., Y. Wu. 2008. Social preferences and supply chain performance: An experimental study. *Management Science* **54**(11) 1835-1849.

Lurie, N. H., J. M. Swaminathan. 2009. Is timely information always better? The effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes* **108**(2) 315-329.

Nahmias, S. 2009. *Production and Operations Analysis.* McGraw-Hill International Sixth Edition.

Özer, Ö., Y. Zheng, K.Y. Chen. 2011. Trust in information sharing. *Management Science* **57**(6) 1111-1137.

Padmanabhan, V., I. P. L. Png. 1995. Returns policies: Make money by making good. *Sloan Management Review* **37**(1) 65-72.

Pasternack, B. 1985. Optimal pricing and returns policies for perishable commodities. *Marketing Science* **4** 166-176.

Pavlov, V., E. Katok. 2009. Fairness and coordination failures in supply chain contracts. *Management Science*, Working Paper.

Petruzzi N. C., M. Dada. 1999. Pricing and the Newsvendor Problem: A Review with Extensions. *Operations Research* **47**(2) 183-194.

Porteus, E. L. 2002. *Foundations of Stochastic Inventory Theory*. Stanford University Press, Stanford, California.

Rosenfield, D. 1986. Optimal management of tax-sheltered employee reimbursement programs. *Interfaces* **16** 68-72.

Schultz, K. L., L. J. Thomas, J. O. McClain, L. W. Robinson. 2007. The use of framing in inventory decisions. *Johnson School Research Paper Series* **02-07**.

Schweitzer, M. E., G. P. Cachon. 2000. Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence. *Management Science* **46**(3) 404-420.

Siegel, S. 1956. *Nonparametric Statistics for the Behavioral Sciences*. New York: McGraw-Hill

Simchi-Levi, D., P. Kaminsky, E. Simchi-Levi. 2008. *Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies* (Third Edition). McGraw Hill, New York, NY.

Spengler, J. J. 1950. Vertical integration and antitrust policy. *The Journal of Political Economy* **58**(4) 347-352.

Steckel, J. H., S. Gupta, A. Banerji. 2004. Supply chain decision making: Will shorter cycle times and shared point of sale information necessarily help? *Management Science* **5**(4) 458-464.

Sterman, J. 1989. Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science* **35**(3) 321-339.

Su, X. 2008. Bounded rationality in newsvendor models. *Manufacturing & Service Operations Management* **10**(4) 566-589.

Taylor, T. 2002. Supply chain coordination under channel rebates with sales effort effects. *Management Science* **48**(8) 992-1007.

Tirole, J. 1998. A theory of collective reputations (with applications to the persistence of corruption and to firm quality). *Review of Economic Studies* **63** 1–22.

Tomlin, B. 2003. Capacity investments in supply chains: Sharing the gain rather than sharing the pain. *Manufacturing & Service Operations Management* **5**(4) 317-333.

Tsay, A. A. 1999. The quantity flexibility contract and supplier-customer incentives. *Marketing Science* **45**(10) 1339 –1358.

Wang, C. X., S. Webster. 2009. The loss-averse newsvendor problem. *Omega* **37**(1) 93-105.

Weatherford, L. R., P. E. Pfeifer. 1994. The economic value of using advance booking of orders. *Omega* **22** 105-111.

APPENDICES

Appendix A Main Script Code in Buyback Experiments

```
// Define Player List
        Players p1,p2,p3,p4,p5,p6,p7,p8,p9,p10,p11,p12,p13,p14,p15,p16;
        Integer nplayer = 16;   //number of players
// Declare variables
        Script("c:\program files\hp mums\Scripts\buyback\var-model.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\var-dummy.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\var-state.cfg");
// Set parameter value
        Script("c:\program files\hp mums\Scripts\buyback\dat-parameter.dat");
// Define inputs
        Script("c:\program files\hp mums\Scripts\buyback\def-input.cfg");
//Stage logon
        Script("c:\program files\hp mums\Scripts\buyback\stage-logon.cfg");
// Game stages
        Script("c:\program files\hp mums\Scripts\buyback\stage-start.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-setgrid.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-predisplay.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-fetchdata.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-exchange.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-results.cfg");
        Script("c:\program files\hp mums\Scripts\buyback\stage-periodend.cfg");
Stage writedb {   // no db write statements in debug
                Script("c:\program files\hp mums\Scripts\buyback\stage-dblog-
period.cfg");
                if (stage=1)
                { End;}
                else
                {Goto start;}
}
```

Appendix B The Script dat-parameter.dat in Buyback Contract Experiments

```
stage setparameter
{
	if (period=1 & stage=1)
	{	// parameters start here
		wholesalegiven = 0;
		buybackgiven = 0;

		price = 250;
		unitcost = 50;
		wholesale = 0;
		buyback = 0;
		mindemand = 40;
		maxdemand = 230;		//parameters end here

		// manufacturer's stage description
		stagedesc[0,1] = "Wholesale and buyback price selection";
		stagedesc[0,2] = "Waiting for the retailer";
		stagedesc[0,3] = "Period results";

		// retailer's stage description
		stagedesc[1,1] = "Waiting for manufacturer";
		stagedesc[1,2] = "Stock quantity decision";
		stagedesc[1,3] = "Period results";

		numman = int(nplayer/2);
		numret = nplayer - numman;
	}

	//allocation of fixed roles and variable partners
	if (stage=1)
	{
	matched=0;
	pos1=0;
	pos2=0;
		 for (i=0; i<nplayer/2; i=i+1)
		{
			allocation1[i] = -1;
		}
		for (i=0; i<nplayer/2; i=i+1)
		{
			allocation2[i] = -1;
		}
		for (i=0; i<nplayer/2; i=i+1)
		{
```

```
            pos1 = int(nplayer/2*random);
            if (pos1 = nplayer/2)
            {
                pos1 = nplayer/2-1;
            }


            if (allocation1[pos1] = -1)
            {
                allocation1[pos1] = i;
            }
            else
            {
                while (allocation1[pos1] <> -1)
                {
                    pos1 = (pos1 + 1) % (nplayer/2);
                }
                allocation1[pos1] = i;
            }
        }

        for (i=0; i<nplayer/2; i=i+1)
        {
            pos2 = int(nplayer/2*random);
            if (pos2 = nplayer/2)
            {
                pos2 = nplayer/2-1;
            }

            if (allocation2[pos2] = -1)
            {
                allocation2[pos2] = i+nplayer/2;
            }
            else
            {
                while (allocation2[pos2] <> -1)
                {
                    pos2 = (pos2 + 1) % (nplayer/2);
                }
                allocation2[pos2] = i+nplayer/2;
            }
        }


        for (i=0; i<nplayer/2; i=i+1)
        {

match[allocation1[i]]=allocation2[i];
match[allocation2[i]]=allocation1[i];
```

```
        role[allocation1[i]] = 0;  //manufacturer
        role[allocation2[i]] = 1;  //retailer

        demand[allocation1[i]] = mindemand + int((maxdemand -
mindemand)*random);
        demand[allocation2[i]] = 0;
                }


                if (wholesalegiven = 1  &  buybackgiven = 1)
                {
                        for (i=0; i<nplayer; i=i+1)
                        {
                                if (role[i] = 0)
                                {
                                        wholesaleset[i] = wholesale;
                                        buybackset[i] = buyback;
                                }
                                else
                                {
                                        wholesaleset[i] = -1;
                                        buybackset[i] = -1;
                                }
                        }
                }

                if (wholesalegiven = 1  &  buybackgiven = 1)
                {
                        stage = 2;     // advance to stage 2 right away
                }
        }
}
```

Appendix C Instructions for Buyback Contract Experiments with Short-Run Relationship

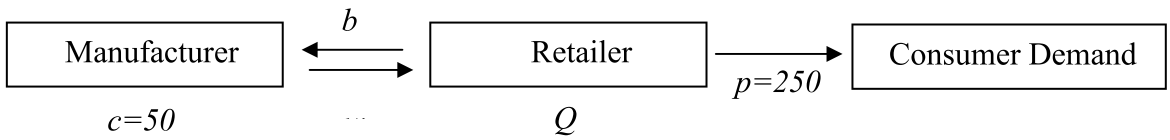
Instructions for Buyback Contract Experiments

March 23th, 2011

Random Match

Scenario

We consider two independent firms: a manufacturer and a retailer. The manufacturer produces a certain product. The retailer buys the product from the manufacturer by paying a ***wholesale price w*** per unit, and sells it to consumers at a ***retail price p=250***. Consumer demand is distributed uniformly *between 40 and 230*. That is, demand is equally likely to be an integer value between 40 and 230. After the demand is realized, the manufacturer buys back the products that the retailer cannot sell by paying the retailer ***buyback price b*** per unit.



The game has three stages:

Stage-1: The manufacturer determines the wholesale price, *w* and the buyback price, *b*. The wholesale price cannot be larger than the retail price *p=250*. The buyback price cannot be larger than the wholesale price.

Stage-2: Given the wholesale price and buyback price decisions of the manufacturer, the retailer determines his ***stock quantity, Q***. The retailer orders this quantity of products from the manufacturer. The manufacturer produces the products by incurring a ***unit production cost c=50***, and sends them to the retailer. The retailer stocks these products prior to the selling season. The retailer's stock quantity can be either zero or lie between 40 and 230, the maximum consumer demand value.

Stage-3: Random consumer demand is realized as "*d*". The retailer's ***sales quantity*** is the minimum of his stock quantity and the realized demand: $\min\{Q, d\}$. Depending on whether the demand is greater or less than retailer's stock quantity, two cases are possible:

- If $d>Q$, then *(d-Q)* units of demand will be unsatisfied (***unsatisfied demand***)
- If $d<Q$, then *(Q-d)* products will be unsold at the retailer (***leftover products***). The manufacturer will buy back these units from the retailer.

The retailer's payoff is calculated as $p * \min\{Q, d\} - w * Q + b * [Q - \min\{Q, d\}]$.
The manufacturer's payoff is calculated as $(w - c) * Q - b * [Q - \min\{Q, d\}]$.
Note that there are three decisions in the game: The manufacturer determines w and b, and then the retailer determines Q.

<u>Experiment Preparation</u>

- The experiments will take place at the CAFÉ (Center for Applied Finance Education) computer lab at the G-floor of the FMAN building.
- Please come to the experiments on-time so that we can start and finish on time.
- You will play a pilot experiment to solidify your understanding of the software.
- Please do not open any other program, including other browser windows, during the experiments.
- Please enter "integer values" for all decisions, and pay attention to the data entry rules.

<u>The Experiment</u>

- In the experiments, you will play the role of either a manufacturer or a retailer for a number of "periods". Your role will be fixed in all periods of an experiment. In each period, the server will randomly match each manufacturer with a retailer. That is, you will be (most likely) playing with different opponents at each period. You will not know with whom you are matched.
- The periods are independent of each other. For example, inventory is not carried from one period to the next. Only your payoff will accumulate over periods.

<u>A Sample Screenshot</u>

Figure 0.1 illustrates how the retailer's screen will look like at stage 2.

- The large table in the middle of the screen is your "**decision support tool**" (to be explained).

- The yellow box on the upper left presents general information including the period number, your current role, the wholesale price, and the buyback price that were set at stage 1. The box also presents two game parameters that are given and fixed throughout all periods (unit production cost, and retail price).
- The blue box in the upper right presents information on the last period.
- The pink box in the bottom is where you “submit” your decision to the server. You enter your decision value into the related gray box, hit “enter” and then click on the green “Submit” button at the bottom (that will be visible during experiment). The submit button is activated only after you enter a valid decision and hit enter (or, click somewhere in the screen). Invalid entries will cause warnings.
- Note that the cells in which you can enter values are the ones with “gray” background.
- You can check the results of previous periods by clicking the “Historical Results” tab in the bottom. This will open a second worksheet with the titles seen in Figure 0.2:

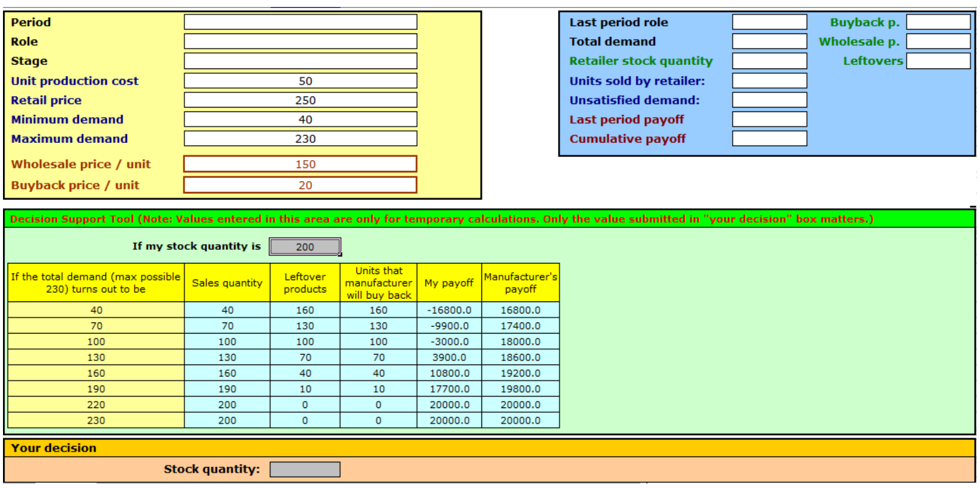


Figure 0.1 Retailer’s Screen at Stage 2

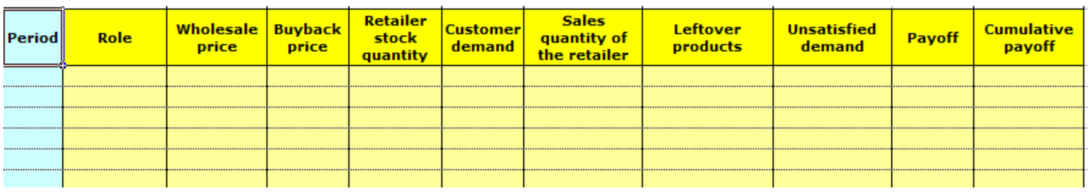


Figure 0.2 Historical Results Screenshot

<u>The Decision Support Tool</u>

Before you submit a decision, you can use the "what-if" decision-support tool provided to you. This tool allows you to calculate the outcome for certain values of your decision, your opponent's decision, and for specific realizations of the consumer demand. *Note that the values you enter in this area are only for your temporary calculations.* The only value that goes to the server (i.e., that is recorded) is the one you submit in the "stock quantity" box that you will find at the bottom of the screen.

The retailer's decision support tool can be seen in Figure 0.3. You may enter a "stock quantity" value in the top gray cell. To help you visualize the possible outcomes if you really set this stock quantity, the table in the decision support tool summarizes the outcome for different consumer demand realizations (*d=40, 70, …, 230*), each in a row.

In the example above, the retailer's stock quantity is entered as 200. We observe from the table that if consumer demand turns out to be, for example, 130, you (retailer) will sell 130 units because the demand is smaller than the stock quantity. You leftover inventory will be 200-130=70 units. The manufacturer will buy back these units. Since you satisfied all consumer demand, there will be no unsatisfied consumer demand.

Compare this with the outcome if consumer demand turns out to be 220. In this case, you (the retailer) will sell all of your 200 units, and there will be zero leftover inventory. Unsatisfied demand will be 220-200=20 units. As you sell your entire stock quantity, the manufacturer will not buy back any inventory. The last two columns provide your payoff and the manufacturer's payoff. At stage 1, the manufacturer's decision support tool will look like below:

If my wholesale price is	150
and my buyback price is	20
and retailer's stock quantity is	200

If the total demand (max possible 230) turns out to be	Retailer's sales quantity	Leftover products at the retailer	Units that I should buy back	My payoff	Retailer's payoff
40	40	160	160	16800.0	-16800.0
70	70	130	130	17400.0	-9900.0
100	100	100	100	18000.0	-3000.0
130	130	70	70	18600.0	3900.0
160	160	40	40	19200.0	10800.0
190	190	10	10	19800.0	17700.0
220	200	0	0	20000.0	20000.0
230	200	0	0	20000.0	20000.0

Figure 0.3 Manufacturer's Decision Support Tool at Stage 1

At this stage, you (the manufacturer) will submit your wholesale price and buyback price. However, in order to use the decision support tool, you also need to guess what stock quantity the retailer might determine at stage 2.

Appendix D Manufacturer's Screen at Stage 1

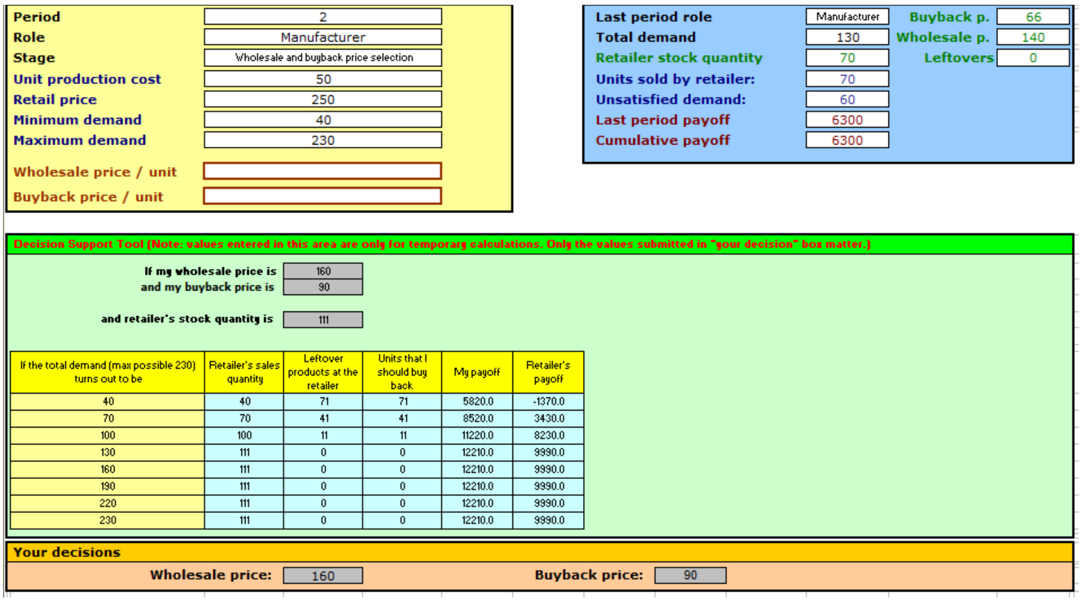
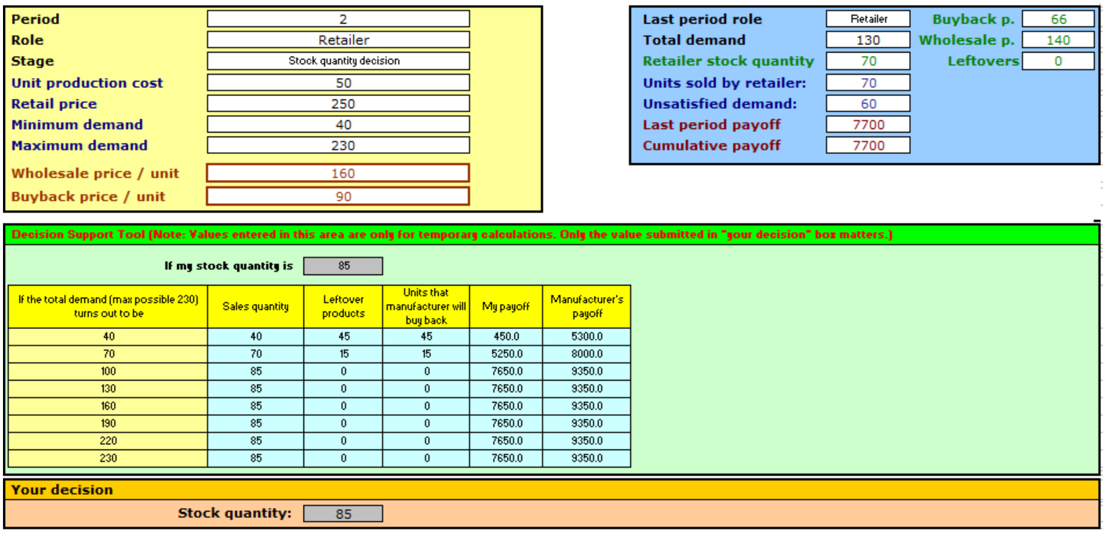


Figure 0.4 Manufacturer's Screen at Stage 1 Screenshot

Appendix E Retailer's Screen at Stage 2



Period	2
Role	Retailer
Stage	Stock quantity decision
Unit production cost	50
Retail price	250
Minimum demand	40
Maximum demand	230
Wholesale price / unit	160
Buyback price / unit	90

Last period role	Retailer	Buyback p.	66
Total demand	130	Wholesale p.	140
Retailer stock quantity	70	Leftovers	0
Units sold by retailer:	70		
Unsatisfied demand:	60		
Last period payoff	7700		
Cumulative payoff	7700		

Decision Support Tool (Note: Values entered in this area are only for temporary calculations. Only the value submitted in "your decision" box matters.)

If my stock quantity is 85

If the total demand (max possible 230) turns out to be	Sales quantity	Leftover products	Units that manufacturer will buy back	My payoff	Manufacturer's payoff
40	40	45	45	450.0	5300.0
70	70	15	15	5250.0	8000.0
100	85	0	0	7650.0	9350.0
130	85	0	0	7650.0	9350.0
160	85	0	0	7650.0	9350.0
190	85	0	0	7650.0	9350.0
220	85	0	0	7650.0	9350.0
230	85	0	0	7650.0	9350.0

Your decision

Stock quantity: 85

Figure 0.5 Retailer's Screen at Stage 2 Screenshot

Appendix F Results Screen

Manufacturer Screen

Period	Role	Wholesale price	Buyback price	Retailer stock quantity	Customer demand	Sales quantity of the retailer	Leftover products	Unsatisfied demand	Payoff	Cumulative payoff
1	Manufacturer	140	66	70	130	70	0	60	6300	6300
2	Manufacturer	160	90	85	110	85	0	25	9350	15650

Figure 0.6 Manufacturer's Historical Result Sheet Screenshot

Retailer Screen

Period	Role	Wholesale price	Buyback price	Retailer stock quantity	Customer demand	Sales quantity of the retailer	Leftover products	Unsatisfied demand	Payoff	Cumulative payoff
1	Retailer	140	66	70	130	70	0	60	7700	7700
2	Retailer	160	90	85	110	85	0	25	7650	15350

Figure 0.7 Manufacturer's Historical Result Sheet Screenshot

Appendix G Mean Differences Between the Experiments with Null Orders and without Null Orders

Table 0.1 Mean Differences between the Experiments with Null Orders and without Null Orders in Buyback Contracts

		With Null Orders					**Without Null Orders**				
		w	**b**	**Q**	**Mfg. Prof.**	**Ret. Prof.**	**w**	**b**	**Q**	**Mfg. Prof.**	**Ret. Prof.**
	Predicted	*247*	*246*	*183*	*22,790*	*333*	*247*	*246*	*183*	*22,790*	*333*
Exp.	**# of rej.**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**
b1a	3	181	81	127	13,797	5,229	180	82	129	14,066	5,350
b1b	15	186	99	113	12,530	4,290	184	94	121	13,362	4,616
b2a	2	163	50	124	12,568	6,668	163	51	125	12,667	6,736
b2b	13	172	77	125	12,428	5,786	170	76	132	13,090	6,152

Table 0.2 Mean Differences between the Experiments with Null Orders and without Null Orders in Wholesale Price Contracts

		With Null Orders				**Without Null Orders**			
		w	**Q**	**Mfg. Prof.**	**Ret. Prof.**	**w**	**Q**	**Mfg. Prof.**	**Ret. Prof.**
	Predicted	*176*	*96*	*12,126*	*5,011*	*176*	*96*	*12,126*	*5,011*
Exp.	**# of rej.**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**
w1a	5	155	115	11,813	6,423	154	118	12,076	6,554
w1b	19	159	105	11,240	5,231	159	115	12,390	5,705
w1c	13	150	116	11,234	6,301	149	123	11,935	6,707
w2a	6	150	124	11,673	7,256	149	128	12,017	7,540
w2b	0	146	139	13,120	7,003	146	139	13,120	7,003
w2c	6	159	119	12,181	6,904	157	123	12,559	7,114

Appendix H Autocorrelation Results for Experiment b1a

Table 0.3 Autocorrelation Results for w(t) and b(t) for the First and the Last Ten Periods in Experiment b1a

		w(t)				**b(t)**			
		Periods 1-10		**Periods 21-30**		**Periods 1-10**		**Periods 21-30**	
	Lag	**Autocor**	**Sign.**	**Autocor**	**Sign.**	**Autocor**	**Sign.**	**Autocor**	**Sign.**
Mfg-1	1	0.078	0.776	-0.044	0.872	0.475	**0.083**	-0.096	0.726
	2	-0.319	0.447	-0.118	0.889	-0.050	0.218	0.084	0.892
	3	-0.236	0.464	-0.138	0.905	-0.075	0.370	0.006	0.973
Mfg-2	1	0.692	**0.011**	-0.095	0.728	0.647	**0.018**	0.304	0.267
	2	0.334	**0.018**	-0.117	0.849	0.408	**0.018**	-0.007	0.539
	3	0.182	**0.035**	-0.139	0.883	0.065	**0.043**	-0.230	0.544
Mfg-3	1	0.100	0.715	0.407	0.137	0.693	**0.011**	-0.158	0.565
	2	-0.073	0.899	0.063	0.321	0.316	**0.019**	-0.026	0.843
	3	-0.109	0.937	-0.057	0.507	-0.058	**0.047**	-0.150	0.866
Mfg-4	1	-0.584	**0.033**	-0.699	**0.012**	0.076	0.782	-0.180	0.511
	2	0.318	**0.048**	0.171	**0.034**	-0.239	0.627	-0.348	0.324
	3	-0.483	**0.018**	0.152	**0.067**	-0.444	0.230	0.258	0.335
Mfg-5	1	0.536	**0.050**	0.683	**0.013**	-0.003	0.990	**Not able to autocorrelate**	
	2	0.071	0.142	0.367	**0.016**	-0.007	1.000		
	3	-0.447	0.062	0.050	**0.040**	-0.700	**0.038**		
Mfg-6	1	0.017	0.950	-0.150	0.584	0.182	0.507	0.268	0.327
	2	-0.391	0.317	-0.175	0.684	-0.227	0.545	0.190	0.472
	3	-0.230	0.361	0.425	0.277	-0.445	0.202	0.310	0.369

Appendix I Autocorrelation Results for Experiment w1a

Table 0.4 Autocorrelation Results for w(t) for the First and the Last Ten Periods in Experiment w1a

<table>
<tr><th></th><th></th><th colspan="4">w(t)</th></tr>
<tr><th></th><th></th><th colspan="2">Periods 1-10</th><th colspan="2">Periods 21-30</th></tr>
<tr><th></th><th>Lag</th><th>Autocor</th><th>Sign</th><th>Autocor</th><th>Sign</th></tr>
<tr><td rowspan="3">Mfg-1</td><td>1</td><td>0.574</td><td>0.036</td><td>0.225</td><td>0.411</td></tr>
<tr><td>2</td><td>0.465</td><td>0.022</td><td>0.200</td><td>0.529</td></tr>
<tr><td>3</td><td>0.057</td><td>0.053</td><td>-0.350</td><td>0.337</td></tr>
<tr><td rowspan="3">Mfg-2</td><td>1</td><td>-0.095</td><td>0.728</td><td>0.233</td><td>0.395</td></tr>
<tr><td>2</td><td>0.038</td><td>0.931</td><td>0.108</td><td>0.638</td></tr>
<tr><td>3</td><td>-0.205</td><td>0.834</td><td>0.024</td><td>0.823</td></tr>
<tr><td rowspan="3">Mfg-3</td><td>1</td><td>-0.088</td><td>0.748</td><td>0.102</td><td>0.711</td></tr>
<tr><td>2</td><td>-0.473</td><td>0.177</td><td>-0.007</td><td>0.933</td></tr>
<tr><td>3</td><td>0.074</td><td>0.314</td><td>-0.008</td><td>0.987</td></tr>
<tr><td rowspan="3">Mfg-4</td><td>1</td><td>0.330</td><td>0.228</td><td colspan="2" rowspan="3">Not able to autocorrelate

The values are same</td></tr>
<tr><td>2</td><td>0.157</td><td>0.403</td></tr>
<tr><td>3</td><td>0.257</td><td>0.400</td></tr>
<tr><td rowspan="3">Mfg-5</td><td>1</td><td>0.163</td><td>0.551</td><td>0.654</td><td>0.017</td></tr>
<tr><td>2</td><td>-0.055</td><td>0.819</td><td>0.429</td><td>0.015</td></tr>
<tr><td>3</td><td>-0.298</td><td>0.588</td><td>0.155</td><td>0.031</td></tr>
<tr><td rowspan="3">Mfg-6</td><td>1</td><td>0.670</td><td>0.014</td><td>0.522</td><td>0.057</td></tr>
<tr><td>2</td><td>0.109</td><td>0.046</td><td>-0.111</td><td>0.148</td></tr>
<tr><td>3</td><td>-0.205</td><td>0.076</td><td>-0.510</td><td>0.041</td></tr>
<tr><td rowspan="3">Mfg-7</td><td>1</td><td>0.326</td><td>0.234</td><td>-0.241</td><td>0.378</td></tr>
<tr><td>2</td><td>0.378</td><td>0.169</td><td>-0.093</td><td>0.636</td></tr>
<tr><td>3</td><td>0.067</td><td>0.303</td><td>0.032</td><td>0.820</td></tr>
<tr><td rowspan="3">Mfg-8</td><td>1</td><td>0.590</td><td>0.031</td><td>0.585</td><td>0.033</td></tr>
<tr><td>2</td><td>0.396</td><td>0.030</td><td>0.305</td><td>0.051</td></tr>
<tr><td>3</td><td>0.061</td><td>0.070</td><td>0.070</td><td>0.110</td></tr>
</table>