EXPERIMENTS ON SUPPLY CHAIN CONTRACTING: EFFECTS OF CONTRACT TYPE AND FAIRNESS CONCERNS

by

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Abstract

In this thesis, we conduct experiments with human decision makers on supply chain contracting. We consider a simple manufacturer-retailer supply chain scenario where the retailer faces the newsvendor problem. Building on Sahin and Kaya (2011), we compare the experimental performance of three contract types (wholesale price, buyback and revenue sharing contracts) between the firms with theoretical predictions, and among each other. We are interested in the manufacturer's contract parameter decisions, the retailer's stock quantity decision, and the firms' profits. In theory, in terms of supply chain efficiency, the buyback and revenue sharing contracts should be equivalent to each other, and should be superior to the wholesale price contract. Our experiments, however, find the wholesale price contract to perform better, and the revenue sharing contract to perform worse than theoretical predictions. The profit distribution between the firms is also much more equitable than predicted. The primary reason for these differences is the biases in retailers' stock quantity decisions. We determine the factors that affect the retailer's stock quantity decision using feature selection and classification techniques. Using a multiple regression model, we show how fairness concerns affect this decision. We also observe short-run relationships between the firms to cause better performance in experiments than long-run relationship, perhaps due to destructive gaming between the firms.

TEDARİK ZİNCİRİ SÖZLEŞMELERİNDE DENEYLER:
SÖZLEŞME TİPLERİ VE ADALET ENDİŞELERİNİN ETKİLERİ

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Anahtar Kelimeler: tedarik zinciri yönetimi, sözleşme, gelir paylaşımı üzerinden sözleşme, davranışsal operasyon, deney, kararlarda yanlılık, adalet endişeleri

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. Sahin ve Kaya (2011) in çalışmalarını da kullanarak üç sözleşme tipinin deneysel performanslarını (satılmayan malların geri alımı üzerinden sözleşme,toptan satış fiyatı üzerinden sözleşme ve gelir paylaşımı üzerinden sözleşme) kuramsal tahminlerle karşılaştırdık. Üreticilerin kontrat parametreleri kararlarının, perakendecilerin stok miktarı kararlarının ve iki firmanın da karları üzerinde durduk. Kuramsal tahminler, gelir paylaşımı üzerinden sözleşme ve geri alım sözleşmesinin tedarik zinciri verimliliği bakımından eşit olması gerektiğini ve bu iki sözleşmenin toptan satış fiyatı üzerinden sözleşmeden daha iyi olduğunu söyler. Bizim deneylerimizde, aksine, toptan satış fiyatı üzerinden sözleşmenin kuramsal tahminlerden daha iyi, gelir paylaşımı üzerinden sözleşmenin ise kuramsal tahminlerden daha kötü sonuç verdiğini gördük. Firmalar arasındaki kar dağılımı beklenenden daha eşitti. Bu farklılıkların ana sebebi perakendecilerin stok miktarı kararlarındaki saplamardır. Perakendecilerin stok miktarı kararlarını etkileyen faktörleri özellik seçme ve sınıflandırma yöntemleriyle seçtik. Çoklu regresyon modeli kullanarak, adalet endişelerinin bu kararı nasıl etkilediğine baktık. 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.

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CHAPTER 1

1. INTRODUCTION

As a result of the outsourcing trend, most products today are produced and delivered to consumers through global supply chains. This vertically disintegrated structure brings certain efficiency benefits compared to a vertically integrated structure (i.e., a single firm). However, at the same time, it introduces the need for “coordination” between the chain members: Each firm in the supply chain aim to maximize its own profit, which can cause conflicts of interest with the other chain members.

A particular coordination issue is observed in supply chains that face uncertain demand for their end product. The problem of matching supply with demand, which is already difficult for a single firm, becomes even more difficult when it involves multiple firms in the chain. Firms often under produce or overproduce due to misaligned incentives, causing not only low profits but also unsatisfied customers.

Due to its importance for practice, a large number of operations management researchers have been studying the issue of supply chain coordination (See, for example Cachon 2003, and Kaya and Ozer 2010). These studies focus on the “contract”, which, by defining the rules of engagement, determines how the profit and risk will be shared between the firms. A well-crafted contract can mitigate the inefficiency in the supply chain by aligning the incentives of the chain members. In fact, it is possible to achieve total coordination within the chain, i.e., single integrated firm performance, by choosing the right contract parameters.

To study contracting in the presence of uncertain demand, most studies in literature consider a simple game-theoretical manufacturer-retailer supply chain model where the retailer faces the well known newsvendor problem. The manufacturer acts first by offering a contract, and hence, determines the overage and underage parameters of the retailer's problem. The model is solved with backwards induction. First, the retailer's optimal stock quantity for a given contract is found using the newsvendor formulation. Then, the manufacturer's optimal contract parameters are calculated, assuming that the retailer will set the newsvendor stock quantity.

Aforementioned analytical models are based on the economic assumption that human beings "aim to maximize only their own benefit and are perfect infallible decision makers who have the information and cognitive capability to always choose the best option among alternatives". These assumptions have been challenged by a high number of experimental studies with human decision makers. Researchers have observed systematic deviations between model predictions and experiment data (Kahneman and Tversky 1979, Tversky and Kahneman, 1981). In fact, theoretical models' inability to explain and predict human behavior has caused a significant gap between supply chain contracting research and practice.

The assumptions in theoretical models can be categorized into those related to individual decision making, and those related to the strategic interaction between two decision makers. The theoretical models make the following two assumptions about how human beings (including firms' managers) make decisions:

- The decision maker aims to maximize his expected utility level. On the contrary, experiments have shown that human beings have other factors in their objective function. They exhibit, for example, loss aversion, ambiguity aversion and regret aversion.

- The decision-maker is rational. That is, he can collect all relevant information, and he has the cognitive ability to choose the best option among alternatives. On the contrary, human beings do not use all relevant information, their cognitive abilities are not that high, and they often resort to satisfying solutions rather than optimizing.

In addition to these, there are the following assumptions from game theory, related to the strategic interaction between two firms:

- The decision maker does not care about the utility level of the decision makers with which he interacts. On the contrary, experiments have shown that human beings care about others' utility in a positive or negative way. Decisions indicate signs of altruism, fairness, trust and reciprocity factors (Fehr, Klein and Schmidt 1999). Social factors such as status and group membership are also effective (Loch and Wu 2008).

Such findings indicate the need to be careful when using theoretical results in studying supply chain contracting.

In this thesis, we conduct experiments with human subjects based on the simple manufacturer-retailer supply chain model. We study the following three well-known supply chain contracts between the firms.

- **Wholesale price contract *(w):*** This contract has only one parameter, the wholesale price. This denotes the price at which the retailer buys the manufacturer's product. Because it has only one parameter, the wholesale price contract cannot coordinate the supply chain.

- **Buyback contract *(w,b):*** In a buyback contract, in addition to the wholesale price w, the manufacturer also determines the buyback price, b, at which he buys back unsold units from retailer. According to theory, the buyback contract can achieve supply chain coordination with a proper combination *(w,b).* Buyback contracts (or returns policies) have been widely used in textile, fashion, publishing, pharmaceuticals and computer software and hardware industries (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).

- **Revenue sharing contract *(w,r):*** In revenue sharing contract, the manufacturer sets a lower wholesale price w, and gains a share of revenue, r, from each unit that the retailer sells to customers. According to theory, the revenue sharing contract can achieve supply chain coordination with proper combination of *(w,r)*. Revenue sharing contract is reported to be used in video rental industry (See Cachon and Lariviere 2005).

The experiments on the wholesale price and buyback contracts were conducted as part of a prior thesis study: Sahin and Kaya (2011). This thesis work adds the revenue sharing contract experiments, and further analysis to answer the following research questions:

- Are the results in revenue sharing contract experiments in line with theoretical predictions?
- How does the experimental performance of the revenue sharing contract compare with the wholesale price and buyback contracts? In theory, the revenue sharing contract is equivalent to the buyback contract, and it is superior to the wholesale price contract in terms of contract efficiency.
- What factors may be effective in the retailer's stock quantity decision deviation from the predicted quantities? Using Weka software, we develop a feature selection and classification method to understand whether subjects consider some factors more than others.
- What is the role of "fairness" factor in retailer's decisions? We measure fairness as the ratio of expected profit of retailer to manufacturer for an offered contract, and develop regression models.

The rest of the thesis is organized as follows: In Chapter 2, we present the related literature. In Chapter 3, we discuss our simple manufacturer-retailer supply chain model, and present its theoretical solution. In Chapter 4, we present the experimental design and procedure. In Chapter 5, we report the results of our experiments. Chapter 6 presents our feature selection and classification study. In chapter 7, we discuss fairness concerns. In Chapter 8, we conclude with discussions and future research suggestions.

CHAPTER 2

2. LITERATURE SURVEY

We consider a simple supply chain composed of a manufacturer and retailer, where the manufacturer's contract determines the retailer's newsvendor problem parameters. We present the relevant literature in three categories. We first present the literature on the newsvendor problem. We then discuss the literature on supply chain coordination, and finally we focus on the literature on the fairness factor. Within each subcategory, we discuss both theoretical and experimental/behavioral studies.

2.1. Literature on the Newsvendor Problem

Newsvendor problem is about a newsboy who has to determine the number of copies of a particular magazine to buy before facing stochastic consumer demand. If demand turns out to be higher than the newsvendor's order quantity (underage situation), the difference becomes lost sales, and the newsvendor loses the opportunity to profit from these sales. If demand turns out to be lower than the newsvendor's order quantity (overage situation), the difference becomes leftover units. The only decision is this single-period problem is the newsvendor's order quantity. Arrow et al. (1951) come up with the famous "critical ratio" solution to the problem. This solution resolves the trade-off between ordering too much and ordering too little by considering the demand distribution and the relative costs of underage and overage.

A common assumption in the newsvendor model is that the newsvendor will act optimally to maximize his expected profit. The missing link in the analytical modeling literature is the question of whether decision-makers do order optimally, and if not, then how to induce the optimal ordering behavior. Empirical studies have shown that decision makers don't behave according to what theory assumes. Corbett and Fransoo (2007) report a survey on how entrepreneurs and small businesses make their inventory decisions. These decisions are found to be partly consistent with the newsvendor model. For high margin products, entrepreneurs and small businesses behave according to the newsvendor model, but not for their best selling products. The respondents behave according to prospect theory: they are risk averse for profits and risk seeking for losses.

Economists have been conducting controlled laboratory experiments to figure out human decision makers' decision processes (Kagel and Roth 1995). They observe that human decision makers are prone to decision errors instead of behaving rationally. The use of experimental methods in operations management have increased rapidly in the last years, leading to the emergence of the "behavioral operations management" field (Bendoly et al. 2006, Gino and Pisano 2008).

The first laboratory experiment about newsvendor problem was conducted by Schweitzer and Cachon (2000). These authors observed that, in high profit condition (where the critical ratio is above 0.5), subjects' average order quantity is less than the optimum order quantity; and in low profit condition (where the critical ratio is below 0.5) subjects' average order quantity is higher than the optimum order quantity. Schweitzer and Cachon refer to this observation as the "pull to center" effect, because in both cases, experimental order decisions are "pulled" towards the mean of the demand distribution, away from the optimal newsvendor quantities. The authors show that the pull to center effect cannot be explained consistently in both high and low margin conditions with a number of possible causes, such as risk aversion, loss aversion or stockout aversion. Instead, Schweitzer and Cachon show that the effect can be explained by the following three heuristics:

- **Mean anchor heuristic** implies anchoring on mean demand, and insufficiently adjusting towards the optimum order quantity.
- **Chasing demand heuristic** implies anchoring on the previous order quantity, and adjusting towards the previous demand realization.
- **Minimizing ex–post inventory error heuristic** implies regretting from not ordering the previous round's demand realization even it was not the optimal decision ex-ante.

Bolton and Katok (2008) also observe pull to center effect in their experiments that consists of three different studies. In first study, they limit the number of ordering options from 100 to 9 and 3 respectively, and conclude that limiting the number of ordering options does not improve performance for both high and low profit conditions. In the second study, they provide information about the foregone decisions, but tracking the foregone options does not help improve performance. In the third study, the authors force subjects to place ten-period standing orders, and they conclude that with standing orders the subjects learn over time by taking long term decisions rather than focusing on short term decisions.

Benzion et al. (2008) study both uniform demand distribution and normal demand distribution in a newsvendor model. The authors observe that subjects biases towards the mean demand diminishes over time and the orders are affected from previous demand realization. Bostian et al. (2008) explain the pull to center effect with an adaptive learning model that considers memory, reinforcement and probabilistic choice factors. They conclude that subjects learn the attractiveness of each order quantity over time based on their past round experiences. Lurie and Swaminathan (2009) show that more frequent feedback does not always improve performance.

The observed decision biases may stem from individual decision making of the subject, or due to strategic decision making between the subjects. Some of the most important individual decision biases studied in the literature are as follows.

- **Risk aversion and Loss aversion**: A risk averse decision maker orders less than the optimum order quantity while a risk seeking decision maker orders more than optimal (Eeckhoudt et al. 1995). Loss averse people tend to avoid situations where probabilities are unknown (uncertainty about uncertainty), and order less than the optimum order quantity, because losses result in larger disutility than the value derived from the same size of gains (Camerer and Weber 1992). Wang and Webster (2006) show that when shortage cost is low, a loss averse decision maker orders less than a rational decision maker. Kahneman and Tversky (1974) analyze the psychophysical determinants of risk aversion and risk seeking.

- **Framing:** Framing, which is related to prospect theory, describes how the subjects decide whether they are facing a loss or a gain. Shultz et al. (2007) conduct experiments to show what kind of framing could trigger better decisions in the newsvendor model. High margin and low margin situations, and positive and negative frames are analyzed. In the positive frame, the gain is emphasized, whereas in the negative frame loss is emphasized. Their experiments find no difference between the positive and negative frames, and no learning effect. Ho and Zhang (2008) analyze whether fixed fee affects nonlinear pricing contracts. They conclude that the fixed fee fails in improving channel efficiency, and that quantity discount contract does better than two part tariff contract, although these two contracts are equivalent in theory. In addition, they show that channel efficiency decreases when loss aversion coefficient increases.

- **Bounded Rationality:** Standard economic theory assumes a perfectly rational decision maker. However, human beings are only boundedly rational (Simon 1982). Su (2008) indicates that pull to center effect can be explained by bounded rationality using a quantal response equilibrium framework. The author concludes that subjects don't always make the best decision, but the good decisions are more likely to be chosen rather than the bad ones. Gaverneni and Isen (2008) use verbal protocol analysis to understand the logic behind the decision makers' decisions in the newsvendor game. They argue that most subjects were successful in calculating underage and overage costs but failed to transform them into optimum order quantity. This study examines subjects' decisions individually, and emphasizes the possible misunderstandings due to use of aggregate data.

- **Irrational Behavior:** Becker-Peth et al. (2011) show that human subjects' orders in an experiment can be predicted accurately even when the subjects are irrational. The authors derive response functions for mean orders, variance of orders and expected profit to predict actual human behavior. They show that contrary to theory, the order quantity not only depends on the critical ratio but also wholesale price and buyback price. In addition, the authors use these response functions instead of the standard newsvendor model to design supply chain contracts.

- **Overconfidence:** An overconfident decision maker estimates a lower demand variance than the true variance. Croson et al. (2008) show that overconfident decision makers make suboptimal decisions. The authors suggest to managers different ways to incentivize overconfident newsvendors. Bolton et al. (2008) show the difference between managers and students when playing the newsvendor game. The authors compare the performance of three subject types: undergraduate students, master students and managers. They conclude that managers don't perform better than two student groups. Graduate students, in particular, are better in using the given information that helps find the optimum solution.

- **Cultural differences:** Experiments have shown that cultural differences affect decision making process. Feng et al. (2010) conduct newsvendor experiments to analyze the cross–national differences between Chinese and American subjects. Chinese subjects' decisions are found to be more anchored to mean demand than American subjects. The authors also examine "thinning set of orders" approach of Bolton and Katok (2008). When the optimum order is one of the middle options rather than the extreme one, supply chain efficiency and the percentage of choice of the optimum order quantity increases. Cui et al. (2011) replicate Gavirneni and Isen (2010)'s thought process study with Chinese students. Chinese students are found to be more adept at dealing with uncertainties by asking questions, probably due to higher uncertainty aversion.

- **Gender Differences:** Vericourt et al. (2011) investigate the effect of gender differences in newsvendor game. Using DOSPERT scale, these authors find that in low profit condition, there is no significant difference between males and females, but in high profit condition, males are more risk seeking. Males tend to set higher quantity than females in high-margin settings due to being less risk averse.

2.2. Literature on Supply Chain Coordination

Supply chain contracting and coordination literature has developed analytical models for many different contract types between supply chain members. In this study, in addition to the simple wholesale price contract, we study the buyback and revenue sharing contracts.

Tsay (1999) analyzes the quantity flexibility contract where retailer commits to order minimum amount of order quantity, and manufacturer guarantees a maximum supply level. Taylor (2002) studies the channel rebate contract. In a linear rebate contract, the manufacturer pays a rebate to the retailer for every unit sold to end customers, whereas in a target rebate contract manufacturer pays a rebate to retailer when the amount that is sold to end customers is beyond a threshold level. Taylor concludes that when demand is independent from retailer's sales effort, a linear rebate contract can achieve channel coordination, but it cannot achieve coordination otherwise. Tomlin (2003) shows that a quantity premium contract in a supplier-manufacturer chain can be highly efficient since it helps a supplier invest in more capacity.

Pasternack (1985) was the first to show that a buyback contract can coordinate a supply chain. He argues that if the manufacturer allows only partial returns, the selling price and return policy is a function of retailer's order quantity; but if the manufacturer can buy back all unsold units (unlimited return policy) then the return policy is independent from retailer's order quantity decision. There are also examples in literature in which the retailer determines both quantity and price at the same time. For example, Emmons and Gilbert (1998) analyzes return policies to figure out what combination of wholesale price and return policy maximizes manufacturer's expected profit. The retailer price increases with increased uncertainty, and the manufacturer gain more profit with buying back unsold units from retailer. Kandel (1996) studies different types of contracts that try to allocate the risk between manufacturer and retailer for the unsold inventory. Two extreme contracts are consignment contract and no return contract. The author shows that manufacturers prefer consignment contracts, where retailers prefer no return contract.

Next, we outline the experimental/behavioral work on supply chain contracting. In this thesis, we use Keser and Paleologo (2004)'s parameter setting as our base model. These authors only study the wholesale price. They do not study long versus short relations between the firms as well. In their experiments, the average wholesale price is observed to be lower than optimum, and the retailers order less than the newsvendor quantity. No evidence is found to support Schweitzer and Cachon's pull to center effect and chasing demand heuristic. Supplier's realized profit is lower than expected, and retailer's realized profit is higher than expected, which implies more equally allocated profits.

Similar to us, Katok and Wu (2009) conducts laboratory experiments to compare wholesale price, buyback and revenue sharing contracts. Different from our experiments, the subjects in these authors experiments play against computerized opponents, rather than playing against each other. Revenue sharing and buyback contracts are observed to perform better than the wholesale price contract, but fail to achieve channel coordination. Retailers' decisions are more likely to show minimizing ex post inventory error than anchoring and insufficiently adjustment heuristic. The difference between buyback and revenue sharing contracts that stem from framing of contract types diminish over time.

Lim and Ho (2007) test the effect of the number of blocks in a contract. They observed that two block tariff contract helps increase supply chain efficiency more than linear price contract, but the increase in efficiency is lower than expected. If the blocks rise to three, the supply chain efficiency goes further, and the manufacturer's profit share increases. The authors propose a Quantal-Response Equilibrium (QRE) model to explain the retailer's sensitivity to counterfactual profits. Haruvy et al. (2011) compare coordinating contracts such as two part tariff (TPT) and minimum order quantity (MOQ) to wholesale price contract. They also compare the efficiency of structured and ultimatum bargaining processes.

Hyndman et al. (2012) analyze the difference between fixed and random matching in coordination games. Fixed matching setting is similar to our long-run experiments, and the random match is similar to our short run experiments. The efficiency of fixed match where is found to be higher in initial periods, but the situation gets reversed at the last five periods of the game. This is explained by the "first impression bias".

By definition, a supply chain consists of multiple decision makers that interact with each other strategically. This interaction is modeled using game theory in literature, however, real human beings do not exactly interact as predicted by game theory. Humans, for example, are influenced by social preferences. Social preferences refer to concerns about the other firm's welfare, reciprocity stem from positive relationship, and desire of a higher relative payoff compared to the other firm when the status is salient. Loch and Wu (2008) designed an experiment in which they try to figure out social preferences and their impact on supply chain coordination. Customer demand is a function of manufacturer's and retailer's selling prices. The authors develop three different experimental conditions as the "control condition" in which players are given simple incentives only, "relationship condition" in which both parties are assumed to have a friendship, and status "seeking condition" in which players are assumed to compete with each other. In relationship condition, both parties are observed to set prices lower than optimum, and in status seeking condition, both parties set selling prices higher than optimum.

In the following subsection, we outline the literature on another important factor related to strategic interaction, "fairness", for which we present a regression study.

2.3. Literature on the Fairness Factor

Research in behavioral economics in the past two decades has shown that "there is a significant incidence of cases in which firms, like individuals, are motivated by concerns of fairness" in business relationships, including channel relationships (Kahneman et al. 1986). Studies in economics and marketing have long documented cases where fairness plays an important role in developing and maintaining channel relationships (See, for example, Okun 1981, Kaufmann and Stern 1988, Geyskens et al. 1998, Corsten and Kumar 2005). For instance, through a large-scale survey of car dealerships in the United States and Netherlands, Kumar et al. (1995) show that fairness is a significant determinant of the quality of channel relationships. Subsequent research has also documented cases where both manufacturers and retailers sacrifice their own margins for the benefit of their counterpart because of fairness concerns (Olmstead and Rhode 1985).

Bowles et al. (1997) show that without rationality, unrelated individuals can earn something with reciprocal behavior in repeated games. They investigate how a change in density of social interaction affects cooperation rates. Cultural differences affect reciprocal fairness and environmental differences affect the way the subjects play the game. Falk et al. (2000) show that in domain of both positively and negatively reciprocal behavior, fairness intention is important. The authors examine fairness as a possible explanation of conflict. They observe that in ultimatum game, subjects make higher offers just because of the rejection risk. Fehr and Gachter (2000) also show that reciprocity and fairness have strong implications in economics. Fehr and Schmidt (2005) argue that people have other-regarding parameters rather than being self interested, that make them care about the other's decisions. In their experiments, they observe both self interested people who don't care the other's welfare as well as other-regarding people.

Fairness factor has recently been studied in supply chain literature as well. Cui et al. (2007) show that when members of supply chain are fair enough, supply chain coordination can be achieved with simple wholesale price contract. Fehr et al. (2007) investigates how fairness concerns affect contract parameters. They show that bonus contracts cannot work well when all parties are selfish. However, when they care about fairness, the firms choose superior bonus contracts rather than incentive contracts. Katok and Pavlov (2009) study an analytical model that focuses on retailer's contract acceptance and rejections. The authors show that if the supplier knows the retailers' fairness concern level, he can coordinate the supply chain, on the other hand, when retailer's fairness concern is a private information, the supplier cannot coordinate the chain. Demirag et al. (2010) analyze nonlinear demand functions such as exponential, constant elasticity, algebraic and logit demand. They show that a wholesale price contract can coordinate supply chain when only the retailer, or both the manufacturer and retailer are concerned about fairness.

CHAPTER 3

3. ANALYTICAL BACKGROUND

In this section, we first present the simple two-firm supply chain setting that we consider, and outline our solution methodology. We then discuss the solution of the integrated supply chain scenario, which provides us with a benchmark. Next, we present the solutions of the disintegrated supply chain under three contract types that we study. These solutions correspond to the "theoretical predictions" to which we compare our experimental observations.

3.1. The Supply Chain Scenario

We consider a manufacturer who produces a certain product, and a retailer who buys the product from the manufacturer and sells it to consumers at a ***sales price of p***. Consumer demand is probabilistic with cdf F(.). Products that are unsold to consumers during the sales season has zero value.

Figure 3.1.1: The Basic Supply Chain

We consider a three-stage game (strategic interaction) between the manufacturer and the retailer:

<u>Stage-1:</u> The manufacturer determines the contract parameters and offers the contract to the retailer. One of the contract parameters is the ***wholesale price, w***. This is the price at which the manufacturer sells his product to the retailer. Depending on the contract type, the contract may include other parameters.

<u>Stage-2:</u> The retailer accepts the contract if it provides him with positive expected profit, and rejects it otherwise. If the retailer rejects the contract, the interaction ends and both firms obtain zero profit. If the retailer accepts the contract, he determines his ***stock quantity Q*** for the product and orders these units from the manufacturer. This is the only ordering opportunity for the retailer. The manufacturer produces this order by incurring a ***unit production cost c*** per product, and delivers the units to the retailer. The retailer stocks these products prior to the selling season.

<u>Stage-3:</u> Random consumer demand is realized as "*D*". Using his stock of product, the retailer satisfies this demand as much as possible. The ***sales quantity*** of the retailer is the minimum of his stock quantity Q and the realized demand. Two cases are possible:

- If demand is higher than retailer's stock quantity (i.e., $D>Q$), then retailer will sell all Q units, and $(D-Q)$ units of demand will be unsatisfied (***unsatisfied demand***). Unsatisfied demand causes no other penalty other than the lost profit margin.
- If demand is less than the retailer's stock quantity, (i.e., $D<Q$), then the retailer will sell D units, and $(Q-D)$ products will be unsold (***leftover products***). These products have zero salvage value.

Each firm makes decisions to maximize its' own ***expected profit*** in the game. Expectation is with respect to the random consumer demand. Note the strategic interaction between two firms: The expected profit of each firm depends not only on its own decision, but also on the other firm's decision and also on the random demand. By offering the contract, the manufacturer makes the first move in this sequential game, and the retailer follows with his stock quantity decision (which can be $Q=0$ in case of contract rejection). To conduct a focused study on contractual incentives, we ignore certain operational (lead times, manufacturer capacity etc.) and strategic (contract negotiations etc.) details in the model.

The Theoretical Solution

The theoretical solution, i.e., the subgame-perfect Nash equilibrium, for this sequential game can be determined using backwards induction. First, one determines the retailer's optimal stock quantity at stage 2 for any given contract offer. The retailer faces the well-known newsvendor problem where the solution follows the famous critical solution formula $Q^*(contract) = F^{-1}\left(\frac{c_u}{c_u + c_o}\right)$. Here, the costs of underage and depend on the manufacturer's contract offer. This formula solves the trade-off between overordering and underordering by considering monetary terms as well as the demand distribution.

Next, using *Q*(contract),* one determines the optimal contract parameters of the manufacturer at stage 1. Similar to standard game-theoretical models, the manufacturer is assumed to foresee the retailer's *Q*(contract)* choice for any contract offer. That is, the manufacturer can solve the retailer's problem. Taking the retailer's *Q*(contract)* reaction into account, the manufacturer determines the contract parameters that maximize his own expected profit.

The manufacturer's objective function is in general not jointly concave in the contract parameters. Hence, one cannot find a closed form solution for the manufacturer's problem. Instead, one can use a numeric procedure to determine the manufacturer's optimal contract parameters through a grid search over possible parameter combinations. Using these contract parameters, one can then calculate the retailer's stock quantity, expected sales quantity, and the expected profits of the two firms. These values characterize the outcome of the game for the given values of model parameters.

3.2. Integrated Supply Chain Solution

Before characterizing the solutions under different contract types, we first determine the integrated supply chain solution which provides an efficiency benchmark. In this scenario, a single decision maker makes all decisions with the objective of maximizing the total supply chain (manufacturer + retailer) expected profit. In business practice, this scenario reflects an integrated firm that owns both the manufacturer and the retailer. The supply chain's problem is formulated as

$$\underset{Q}{maximize}\ \pi_{total}^{sc}(Q) = pE[\min(Q, D)] - cQ\ .$$

This is also a newsvendor problem. Note that the contract parameters are not relevant for the supply chain's problem. The stock quantity that maximizes the supply chain's expected profit is:

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

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

$$\pi_{total}^{sc}(Q^{sc}) = pE[\min(Q^{sc}, D)] - cQ^{sc}. \tag{2}$$

In this thesis, we study *decentralized* supply chains where the manufacturer and the retailer are two independent firms. Such decentralized decision making by two separate firms result in inefficiencies because each firm considers only its own profit margin in making decisions, not the total supply chain profit margin. This is known as the "double marginalization' problem (Spengler 1950).

The maximum total expected profit achievable in a decentralized supply chain under any contract is given by the level in Equation (2. This is referred to as the *integrated firm profit*. The ratio of the total expected profit level under a contract to integrated firm profit is known as *contract efficiency*. A contract that achieves 100% efficiency is said to be *coordinating* the supply chain. In this case, the incentives of the firms are aligned, and inefficiencies due to double marginalization are eliminated. Coordination requires the retailer to choose the integrated firm stock quantity Q^{sc}. Any other stock quantity choice will cause suboptimal total expected profit level in the supply chain.

While the retailer's stock quantity decision determines the total supply chain profit, the manufacturer's contract parameter decision has three roles:

- *Inducing the retailer's Q choice:* Manufacturer's contract parameters affect the retailer's stock quantity Q choice through the newsvendor formula. If the contract parameters satisfy certain conditions, they may cause the retailer to choose Q^{sc}, achieving coordination. The manufacturer, however, aims to maximize his own profit rather than maximizing the total supply chain profit.

- *Profit sharing:* The contract parameters determine how the total profit will be shared (in expectation) between the two firms. For example, a high wholesale price increases the manufacturer's expected profit share at the expense of the retailer's share.

- *Risk sharing:* The retailer faces underage/overage risk due to probabilistic consumer demand. The contract parameters in the buyback and revenue sharing contracts determine how much of this risk is shared by the manufacturer.

We present the theoretical solution for a given customer demand distribution with cdf F(.). In our experiments, consumer demand is Uniformly distributed between (D_{max}, D_{min}). For this distribution, one can further characterize the optimal stock quantity of the retailer as

$$Q^{sc}(contract) = \left(\frac{c_u}{c_u + c_o}\right) * (D_{max} - D_{min}) + D_{min}\,.$$

3.3. Solution under Wholesale Price Contract (WSP)

This contract has only one parameter, the wholesale price value w. Given the contract (w), the retailer's problem is

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

The retailer's optimal stock quantity satisfies

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

(3)

Comparing Equations 1 and 3, we observe that the wholesale price contract cannot coordinate the supply chain unless the manufacturer sets w=c. Such a choice is unlikely because it yields zero expected profit to the manufacturer. Having only one parameter, this contract type fails to align the incentives of the two firms.

For uniformly distributed demand, the unique stock quantity solution becomes

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

Substituting $Q^{w}(w)$, the manufacturer's problem becomes

$$\underset{\mathrm{w}}{maximize}\ \pi_{m}^{w} = (\mathrm{w}-\mathrm{c})\ \mathrm{Q^{w}}\ .$$

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

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

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

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

3.4. Solution under Revenue Sharing (RS) Contract

Under a revenue sharing contract *(w,r)*, the retailer pays the manufacturer a ***revenue share r*** per unit sold to customers, in addition to the standard wholesale price he pays per unit he orders. Under this contract, the manufacturer usually offers a lower wholesale price compared to a wholesale price contract because he also charges the retailer for units sold to customers. The retailer's problem becomes

$$\underset{Q}{maximize}\ \pi_r^{rs}(Q) = (p-r)E[\min(Q,D)] - wQ.$$

Under the revenue sharing contract *(w,r)*, the retailer's cost of underage becomes *p-w-r* while the cost of overage is w. The retailer's optimal stock quantity is:

$$Q^{rs}(w,r) \;=\; F^{-1}\left(\frac{c_u}{c_u+c_o}\right) \;=\; F^{-1}\left(\frac{p-w-r}{p-r}\right). \tag{4}$$

Comparing Equations 1 and 4, one can show that the supply chain will be coordinated if the revenue sharing contract parameters satisfy $\mathrm{r} = \mathrm{p(c-w)/c}$. However, recall that the manufacturer's objective is to maximize his own expected profit rather than supply chain coordination. Substituting $Q^{rs}(w,r)$, the manufacturer's problem becomes

$$\underset{w,\,r}{maximize}\ \pi_m^{rs} = (w-c)Q^{rs} + rE[min(Q^{rs},D)].$$

3.5. Solution under Buyback (BB) Contract

With this contract, the manufacturer buys back unsold units from the retailer at the end of the sales season by paying a buyback price b per unit. By buying back unsold units, the manufacturer reduces the retailer's cost of overage, encouraging the retailer to set a higher stock (order) quantity. The retailer's problem becomes

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

Under the buyback contract *(w,b)*, the retailer's cost of overage becomes *w-b* while the cost of underage is *p-w*. The retailer's optimal stock quantity is found as:

$$Q^b(w,b) = F^{-1}\left(\frac{c_u}{c_u+c_o}\right) = F^{-1}\left(\frac{p-w}{p-b}\right). \tag{5}$$

Comparing Equations 1 and 5, one can show that the supply chain will be coordinated if the buyback contract parameters satisfy $b = \frac{p(w+c)}{p-c}$.

Substituting $Q^b(w,b)$, the manufacturer's problem becomes

$$\underset{w,\,b}{maximize}\ \pi_m^b = (w-c)Q^b - bE[Q^b - min(Q^b, D)].$$

3.6. The Solutions under Our Parameter Setting

We consider the following model parameter values:

- Unit production cost, $c = 50$.
- Retail price, $p = 250$.
- Demand uniformly distributed between 40 and 230, and can take only integer values.
- All decision variables are integers.

This parameter setting is the same as the one used by Keser and Paleologo (2004). Given these parameters, the manufacturer's wholesale price satisfies $0 \le w < p = 250$. For a given w, the revenue share price in an RS contract satisfies $0 \le r \le 250 - w$. Likewise, the buyback price in a BB contract satisfies $0 \le b \le w$.

The subgame-perfect equilibrium solutions under the three contracts are summarized in Table 3.6.1 below.

Table 3.6.1: Solutions Under the Three Contracts

Type of Contract	**Total Profit**	**Contract Efficiency**	**Mfg. Profit**	**Retailer Profit**	**w**	**b**	**r**	**Q**
Wholesale Price	17,137	74.00%	12,126	5,011	176	--	--	96
Revenue Share	23,117	98.50%	22,784	333	1	--	246	183
Buyback	23,117	98.50%	22,784	333	247	246	--	183

We observe the manufacturer's optimal solution under the buyback and revenue sharing contracts to dominate the solution under wholesale price contract in terms of total profits. This is primarily due to differences between the retailer's stock quantities. In fact, the efficiencies of the buyback contract and revenue sharing contracts are close to 100%, which is good news from the supply chain point of view. However, the profit distributions under these contracts are quite unbalanced. Almost all profit is going to manufacturer. The wholesale price contract, on the other hand, while inefficient, offers the retailer a decent profit level.

Note that these theoretical results assume that

1. The retailer will accept any contract that provides him with nonzero expected profit;
2. The retailer will determine his stock quantity according to the newsvendor formula;
3. The manufacturer will be able to foresee the retailer's stock quantity choice and choose contract parameters accordingly;
4. Each firm's objective is to maximize its own expected profit.

As we will discuss in our experimental study, 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 experiment procedure. We also briefly summarize our approach to data analysis.

4.1. Experimental Design

This study involves 14 experimental sessions. Each experiment consists of 30 independent periods. In each period, the supply chain scenario described in Section 3.1 is played between two human subjects that play the roles of manufacturer and retailer.

The experimental design is illustrated in Table 4.1.1, where *n* denotes the number of subjects. We study three different contract types (wholesale price, revenue sharing and buyback contracts) and two relationship length types (long run and short run). In long run experiments, the same manufacturer-retailer pair interacts throughout all 30 periods, whereas in short run experiments, the pairs are re-determined in each period.

Table 4.1.1: Experimental Design and Number of Subjects

		Contract Type		
		Buyback	**Wholesale price**	**Revenue Sharing**
Relationship Length	**Long run**	Experiment b1a, n=12 Experiment b1b, n=16	Experiment w1a, n=16 Experiment w1b, n=16 Experiment w1c, n=16	Experiment r1a, n=12 Experiment r1b, n=16
	Short run	Experiment b2a, n=12 Experiment b2b, n=16	Experiment w2a, n=16 Experiment w2b, n=16 Experiment w2c, n=16	Experiment r2a, n=12 Experiment r2b, n=16

The wholesale price and buyback experiments reported in this thesis were conducted before, and were already reported in Sahin and Kaya (2011). This thesis extends Sahin and Kaya's work by adding the revenue sharing contract experiments, by comparing RS contract experiment data with other contracts, and by presenting further analyses on all three contracts' data.

Next, we explain the experimental procedure using the revenue sharing contract experiments as an example. The wholesale price and buyback contract experiment procedures are similar.

4.2. Experimental Procedure (Revenue Sharing Experiments)

Our experiments are computer-based and were conducted at the CAFE (Center for Applied Finance Education) computer laboratory of Sabancı University, Faculty of Management. This laboratory, which contains 24 dual-screen connected computers, serves as an interactive classroom for the University's graduate program in finance. The experimental model was coded using a special-purpose script language, HP MUMS. Part of the experiment code is provided in Appendix A as a sample.

The experiment was announced to the Spring 2012/2013 semester students of Sabancı University course MS 401. These students had already studied the basic newsvendor problem. Interested students were recruited through an online application system. To provide incentive for experiment attendance and to induce motivated decisions, each subject was given a grade bonus proportional to his/her total profit in the experiment. The bonus grade ranged between 1% and 2.5%, and it was applied to MS 401 course final grade of the student.

The subjects were given detailed instructions a couple of days before the experiment. Sample instructions are provided in Appendix B. Upon arrival to the lab, the subjects were seated randomly in the lab. Next, an experimenter explained the scenario and the software interface on the blackboard to ensure that the instructions are clearly understood, and answered any remaining questions of the subjects. Before starting the actual experiment, the subjects played through three training periods using the experiment interface. These periods data were not recorded. Finally, the real experimental session, which took around two hours, began. The subjects were prohibited from communication during the experiment. Separators were installed at the edges of screens to isolate subjects from each other.

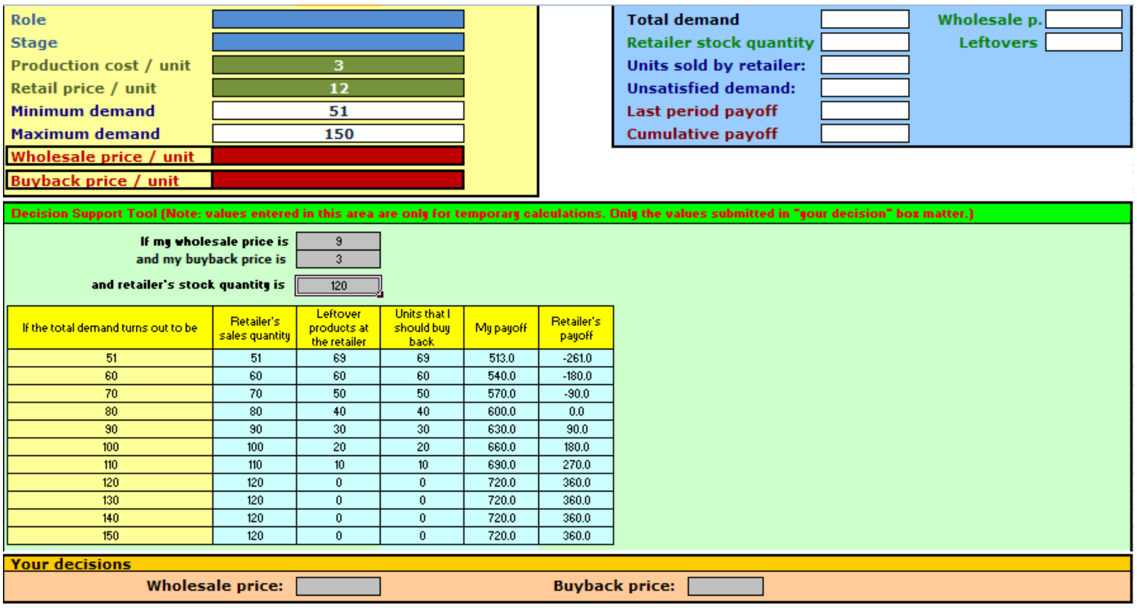
At the beginning of the experiment, the server computer assigns each subject the role of either manufacturer or retailer. The role of a subject stays unchanged throughout the experiment. The server then randomly matches the subjects to form manufacturer-retailer pairs. These pairs stay fixed in "long run relationship" type experiments, whereas the pairs are re-determined in each period in "short run relationship" type experiments.

Each pair plays the supply chain scenario for 30 periods (rounds). The periods are independent of each other. Inventory is not carried from one period to the other, and demand values are not correlated. In each period, the following sequence of events take place, in accordance with our supply chain scenario:

- Each manufacturer determines contract parameters and submits these decisions to the server computer by entering these into relevant boxes in his screen. A sample manufacturer screen is provided in Figure 4.2.1.
- After the server receives all manufacturers' contract decisions, it transmits each manufacturer's decisions to his retailer pair's screen.
- Observing the contract parameters, the retailer determines his stock (order) quantity and submits this decision to the server. The manufacturer is assumed to produce and deliver these units to the retailer prior to the selling season. The retailer may reject the contract by submitting zero quantity. Figure 4.2.2 provides a sample retailer screen.
- The server randomly determines the random consumer demand realization for each pair. Depending on this realization, the sales, leftover quantities and lost sale quantities, as well as profit realizations are calculated. These values are reported to pairs. In fact, the subjects can access their all past periods' results at any point during the experiment using the historical results screen given in Figure.

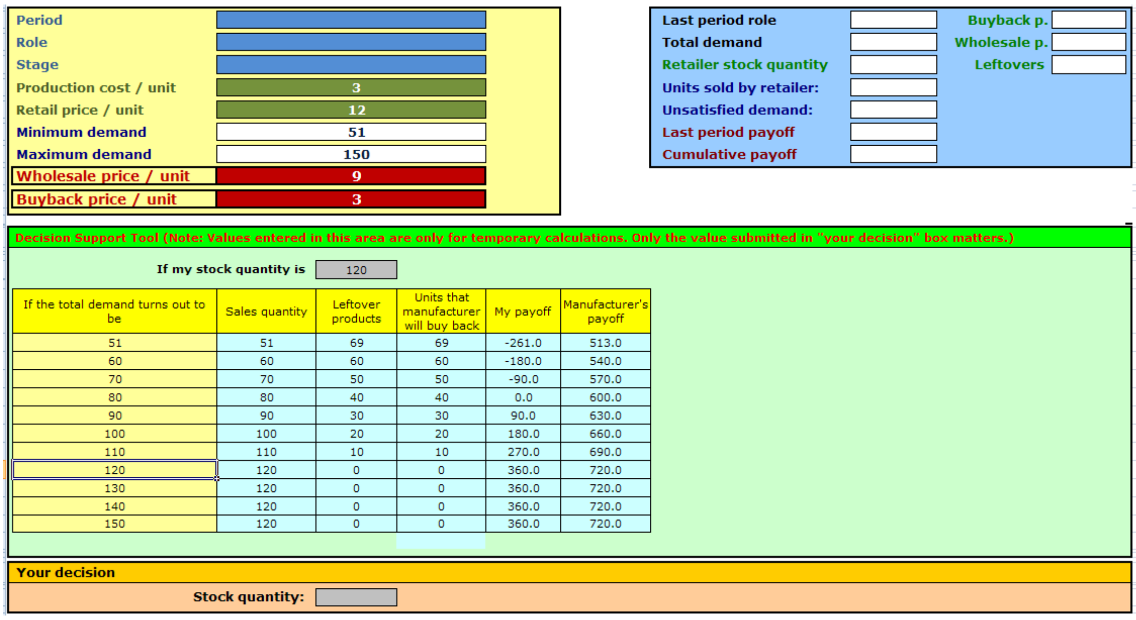
- The server records all results and proceeds to the following period.

Each subject is given around 40 seconds to make his decision in every period. This duration was longer in the initial periods to allow experimentation. As seen in Figure 4.2.1 and Figure 4.2.2, we provide a “decision support tool” (the table in the middle of the screen) to help subjects make decisions. 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, r), 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 B where we provide the instructions.



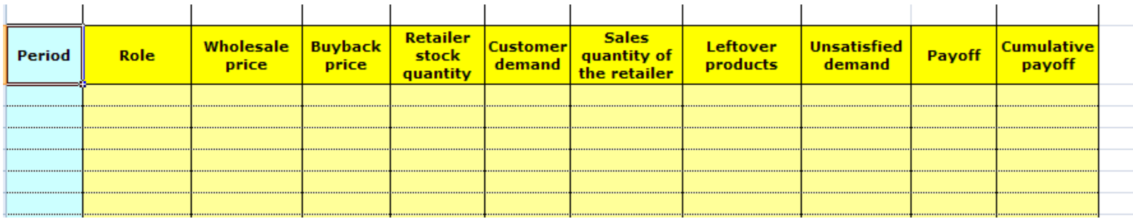
If the total demand turns out to be	Retailer's sales quantity	Leftover products at the retailer	Units that I should buy back	My payoff	Retailer's payoff
51	51	69	69	513.0	-261.0
60	60	60	60	540.0	-180.0
70	70	50	50	570.0	-90.0
80	80	40	40	600.0	0.0
90	90	30	30	630.0	90.0
100	100	20	20	660.0	180.0
110	110	10	10	690.0	270.0
120	120	0	0	720.0	360.0
130	120	0	0	720.0	360.0
140	120	0	0	720.0	360.0
150	120	0	0	720.0	360.0

Figure 4.2.1: Sample Manufacturer Screen



If the total demand turns out to be	Sales quantity	Leftover products	Units that manufacturer will buy back	My payoff	Manufacturer's payoff
51	51	69	69	-261.0	513.0
60	60	60	60	-180.0	540.0
70	70	50	50	-90.0	570.0
80	80	40	40	0.0	600.0
90	90	30	30	90.0	630.0
100	100	20	20	180.0	660.0
110	110	10	10	270.0	690.0
120	120	0	0	360.0	720.0
130	120	0	0	360.0	720.0
140	120	0	0	360.0	720.0
150	120	0	0	360.0	720.0

Figure 4.2.2: Sample 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

Figure 4.2.3: Sample Historical Results Screen

4.3. Experimental Data Analysis

Recall that the outcome of a game is shaped by first the manufacturer's decision, second the retailer's decision and third the realization of random consumer demand. We use the following terms to differentiate the predictions at different levels:

1) **Manufacturer's optimal outcome:** This corresponds to the subgame-perfect equilibrium of the model as explained in Section 3.4. In this outcome, the manufacturer offers the contract ($w^{rs}=1$, $r^{rs}=246$), and the retailer stocks the corresponding newsvendor quantity $Q^{rs}(w^{rs},r^{rs}) = 183$. Manufacturer's expected

profit is 22,784 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 any given period.

2) **Newsvendor prediction (predicted outcome):** In experiments, manufacturers often do not set optimal contract parameters (w^{rs},r^{rs}). We define the "predicted outcome" as the expected outcome of the game given any contract *(w, r)* choice by the manufacturer, assuming that the retailer orders the newsvendor stock quantity $Q^{rs}(w, r)$.
3) **Expected outcome:** Retailer subjects also often deviate from the newsvendor stock quantity decision. For any contract *(w,r)* and retailer's response *Q(w,r),* the "Expected outcome" denotes the expected result with respect to consumer demand distribution.

In our analyses, we compare these prediction values to **realized (observed) outcome.** This is the observed experimental data based on the two firms' decisions and a particular realization of consumer demand.

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. Consistent with the literature, we exclude rejected contract decisions from the main analysis. The information about the rejected contracts are provided separately. Appendix C provides the summary results with and without rejected contracts.

We do not have 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 present the results of our experimental study and compare the results with theoretical predictions. We first make an overall comparison with respect to contract type and relationship length. These comparisons complement the ones reported in Sahin and Kaya (2011) by providing the revenue sharing experiment results. Next, we present detailed analyses on one long run (r1b) and one short-run (r2b) relationship revenue sharing contract experiment sessions.

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 the same number of data points as its number of 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. We exclude the data of the games where the contract is rejected.

Table 5.1.1: Experimental Design

		Contract Type		
		Buyback (BB)	**Wholesale Price (WSP)**	**Revenue Sharing (RS)**
Relationship Length	**Long Run**	b1 experiments 60 data points	w1 experiments 90 data points	r1 experiments 56 data points
	Short Run	b2 experiments 60 data points	w2 experiments 90 data points	r2 experiments 60 data points

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

5.1.1. Revenue Sharing Contract Experiments

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

Table 5.1.2: Comparison of Revenue Sharing Experiments

Revenue Sharing	**Mfg. Optimal**		**Revenue Sharing All (n=116)**	**p - value**	**Long Run (r1, n=56)**	**Short Run (r2, n=60)**	**p - value**
Total Profit	23,117	Mean	18207	**0.000**	17834	18496	0.507
		Median	18275		18120	18345	
		Std	3156		3211	3108	
Mfg. Profit	22,784	Mean	11711	**0.000**	11500	11944	0.505
		Median	11395		11376	11420	
		Std	2036		1934	2162	
Retailer Profit	333	Mean	6497	**0.000**	6335	6553	0.918
		Median	6760		6570	6679	
		Std	2314		2641	1957	
Retailer Predicted Profit	333	Mean	7479	**0.000**	7370	7674	**0.003**
		Median	7384		7036	7722	
		Std	1106		1797	1844	
w	1	Mean	101	**0.000**	108	90	**0.000**
		Median	103		109	85	
		Std	17		19	24	
r	246	Mean	66	**0.000**	58	75	**0.010**
		Median	64		57	82	
		Std	20		16	27	
Q	183	Mean	117	**0.000**	113	128	**0.000**
		Median	116		114	127	
		Std	26		35	39	

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, REVENUE SHARING CONTRACT): The outcome of the interaction will be as described by the manufacturer's optimal solution. Specifically, w=1, r=246, Q=183 with a total profit of 23,117, where the manufacturer gains 22,784 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 revenue share price, and much higher wholesale prices than the manufacturer's optimal solution. Retailer's stock quantities are much lower than those in the optimal solution. Total profit level, which depends on the retailer's stock quantity, is also 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 over time[1] and may develop collaborative strategies. 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 and that the pairs are re-determined randomly in each period. Hence, we expect the partners to act more myopically, leading to opportunistic behavior.

[1] Note that players are not allowed to communicate during experiments.

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

Experimental data rejects this hypothesis. Surprisingly, although not significant, the total profit, manufacturer's profit and retailer's profit are all higher in the short run relationships. 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. Comparing the Revenue Sharing and Wholesale Price Contract Experiments

Here we compare the experimental performances of the revenue sharing and wholesale price contracts. Based on supply chain contracting literature, we expect the revenue sharing 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 revenue sharing contract. This is because the manufacturer is the one who offers contract parameters, and the wholesale price contract is only a special case of the revenue sharing contract with $r = 0$.

HYPOTHESIS-3 (RS-WSP CONTRACT COMPARISON): (3a) Total profit and (3b) the manufacturer's profit will be higher under the revenue sharing contract than under the wholesale price contract.

Table 5.1.3 provides descriptive statistics for the comparison.

Table 5.1.3: Comparison of the Revenue Sharing Contract Experiments with the Wholesale Price Contract Experiments

	Mfg.'s Optimal Solution		Experiment Data			
	Revenue Sharing	WSP		Revenue Sharing All (n=116)	Wholesale Price All (n=180)	p - value
Total Profit	23,117	17,137	Mean Median Std	18,207 18,275 3,156	19,120 19,132 2,895	**0.016**
Efficiency	98.5%	73.7%	Mean Median Std	78.7% 79.0% 13.6%	82.4% 82.4% 3.0%	**0.000**
Mfg Profit	22,784	12,126	Mean Median Std	11,711 11,395 2,036	12,349 12,299 1,364	**0.000**
Retailer Profit	333	5,011	Mean Median Std	6,497 6,760 2,314	6,770 6,778 2,990	0.377
Retailer Predicted Profit	333	5,011	Mean Median Std	7,479 7,384 1,106	7,511 7,426 1,069	0.990
Q	183	96	Mean Median Std	117 116 26	125 124 15	**0.000**

Experiment data rejects Hyphothesis-3a. Contrary to expectation, the total profit under the revenue sharing contract is significantly lower than that under the wholesale price contract. This finding is interesting because the revenue sharing 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 revenue sharing contract is coordinating when $Q^{sc}=192$, with a total supply chain profit of 23,280. The manufacturer's optimal solution with the revenue sharing contract yields a total profit of 23,117, which is quite close to the total profit under coordination. If the manufacturer offered his optimal revenue sharing 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 does not offer revenue sharing contracts that have high contract efficiency at all. The average efficiency of the revenue sharing contracts in experiments is around 79%.

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 82.4%, which is much higher than the theoretical predicted value of 73.4%. Our results support Wu (2013), and Katok and Wu (2009) in reporting that wholesale price contract to performs better than theoretical prediction.

The results are the same for Hypothesis 3b. We observe the revenue sharing contract to decrease both manufacturer's and retailer's (not significantly) profits. Our results contradict Katok and Wu (2009)'s results. In their experiments 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.

Finally, as Table 5.1.4 illustrates, directional comparisons between the wholesale price and revenue sharing contracts are robust if one compares the long run and short run experiments separately. Some of the differences, however, are not significant any more.

5.1.3 Comparing the Revenue Sharing and Buyback Contract Experiments

Here we compare the experimental performances of the revenue sharing and buyback contracts. Based on supply chain contracting literature, we expect the two contracts to be equivalent. Table 5.1.5 provides descriptive statistics for the comparison.

HYPOTHESIS-4 (RS-BB CONTRACT COMPARISON): (4a) Total profit and (4b) the manufacturer's profit will be the same in the revenue sharing contract and the buyback contract.

Table 5.1.4: Comparison of Long-Run and Short-Run Relationship Experiments Between Revenue Sharing and Wholesale Price Contracts

	Long Run Relationship				Short Run Relationship			
		Revenue Sharing (n=56)	**Wholesale Price (n=90)**	**p - value**		**Revenue Sharing (n=60)**	**Wholesale Price (n=90)**	**p - value**
Total Profit	Mean Median Std	17,834 18,120 3,221	18,455 18,347 2,612	0.375	Mean Median Std	18,496 18,345 3,108	19,784 19,881 3,023	**0.007**
Efficiency	Mean Median Std	77.1% 78.3% 13.8%	81.85% 81.57% 2.76%	**0.015**	Mean Median Std	80.0% 79.3% 13.4%	83.0% 83.4% 3.08%	**0.003**
Mfg Profit	Mean Median Std	11,500 11,376 1,934	12,134 11,912 1,443	**0.039**	Mean Median Std	11,944 11,420 2,162	12,565 12,598 1,251	**0.000**
Retailer Profit	Mean Median Std	6,335 6,570 2,641	6,322 6,289 2,702	0.902	Mean Median Std	6,553 6,679 1,957	7,219 7,482 3,204	0.165
Retailer Predicted Profit	Mean Median Std	7,239 7,095 1,025	7,298 7,144 958	0.883	Mean Median Std	7,703 7,550 1,139	7,724 7,770 1,136	0.900
Q	Mean Median Std	105 102 20	119 118 14	**0.000**	Mean Median Std	128 125 26	131 131 13	0.081

Experiment data rejects both Hyphothesis-4a and Hypothesis 4b. Buyback contract performs better than the revenue sharing contract. Yet, note that the efficiency of both contracts are far less than the theoretical prediction. Under the revenue sharing contract, the manufacturers profit is significantly lower, but the retailer's profit is significantly higher than the buyback contract. As indicated by the retailer's predicted profit comparison, the manufacturers offer more favorable contracts under the RS contract. However, the retailers responded with lower stock quantities. The poor performance of the revenue sharing contract may be due to its "framing". The revenue sharing contract requires the retailer to "share" his revenue with the manufacturer, whereas the buyback contract provides safety against unsold items. The retailers may prefer the buyback contract even when the revenue sharing contract offers higher expected profits.

Table 5.1.5: Comparison of the Revenue Sharing Experiments with the Buyback Contract Experiments

	Mfg.'s Optimal Solution		Experiment Data			
	Revenue Sharing	**Buyback**		**Revenue Sharing All (n=116)**	**Buyback All (n=120)**	**p - value**
Total Profit	23,117	23,117	Mean	18,207	19,010	**0.000**
			Median	18,275	18,873	
			Std	3,156	3,386	
Efficiency	98.5%	98.5%	Mean	78.7%	81.8%	**0.000**
			Median	79.0%	81.2%	
			Std	13.6%	14.5%	
Mfg Profit	22,784	22,784	Mean	11,711	13,788	**0.000**
			Median	11,395	13,815	
			Std	2,036	1,104	
Retailer Profit	333	333	Mean	6,497	5,714	**0.016**
			Median	6,760	5,657	
			Std	2,314	2,765	
Retailer Predicted Profit	333	333	Mean	7,479	6,143	**0.000**
			Median	7,384	6,030	
			Std	1,106	1,129	
Q	183	183	Mean	117	127	**0.000**
			Median	116	127	
			Std	26	14	

This result contradicts Wu (2013), who conducted 100-round long run relationship experiments under wholesale price, revenue sharing and buyback contract experiments. She found no significant difference between buyback and revenue sharing contracts in the initial periods of the interaction, but some difference in the latter periods.

As Table 5.1.6 illustrates, the comparisons we make between the two contract types are robust if one focuses only on the long-run relationship experiments. If one considers short-run experiments only, the differences between the stock quantities and retailer profits become insignificant.

Table 5.1.6 Comparison of the Long Run and Short Run Relationship Experiments Between Revenue Sharing and Buyback Contracts

	Long Run Relationship				Short Run Relationship			
		Revenue Sharing (n=56)	Buyback (n=60)	p - value		Revenue Sharing (n=60)	Buyback (n=60)	p - value
Total Profit	Mean	17,834	18,697	**0.017**	Mean	18,496	19,323	**0.008**
	Median	18,120	18,585		Median	18,345	19,076	
	Std	3,211	3,419		Std	3,108	3,351	
Efficiency	Mean	77.1%	80.5%	**0.023**	Mean	80.0%	83.2%	**0.013**
	Median	78.3%	80.0%		Median	79.3%	82.1%	
	Std	13.8%	14.7%		Std	13.4%	14.4%	
Mfg Profit	Mean	11,500	14,267	**0.000**	Mean	11,711	13,309	**0.000**
	Median	11,376	14,489		Median	11,395	13,247	
	Std	1,934	1,276		Std	2,036	604	
Retailer Profit	Mean	6,335	4,983	**0.004**	Mean	6,497	6,444	0.738
	Median	6,570	4,697		Median	6760	6,529	
	Std	2,641	2,663		Std	2314	2,692	
Retailer Predicted Profit	Mean	7,239	5,414	**0.000**	Mean	7,703	6,872	**0.000**
	Median	7,095	5,251		Median	7,550	6,808	
	Std	1,025	791		Std	1,139	929	
Q	Mean	105	125	**0.000**	Mean	128	129	0.280
	Median	102	125		Median	125	129	
	Std	20	15		Std	26	14	

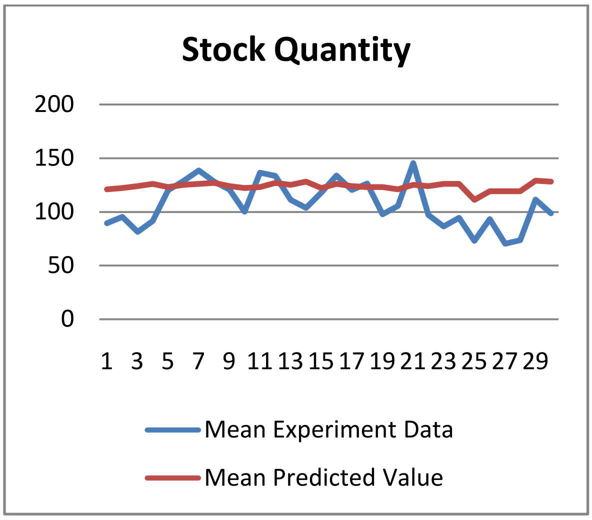
5.2. **Experiment r1b Results (Long run interaction)**

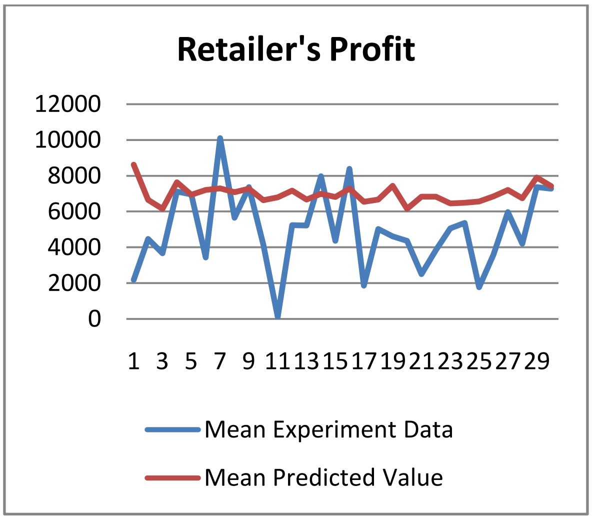
Experiment r1b is one of the long-run interaction experiments under revenue sharing contract. It has seven manufacturer-retailer pairs. Contract rejection is observed in 24 games.

5.2.1 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.

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





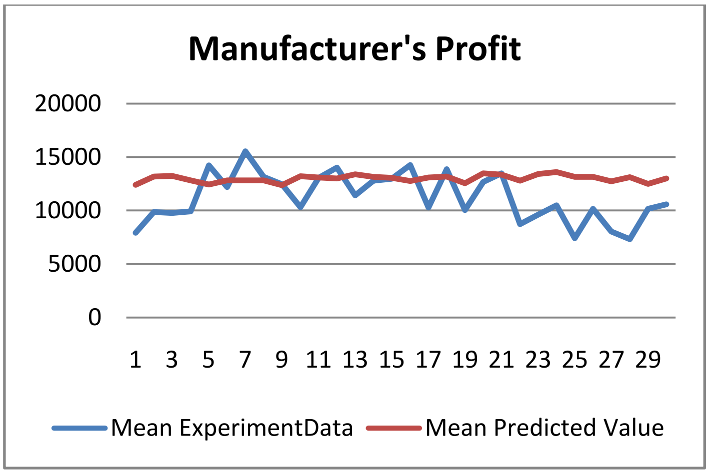


Figure 5.2.1: (a)-(c) Stock Quantity and Firms Profits in Experiment r1b

We observe that stock quantity is lower than predicted. Retailer's profit and manufacturer's profit is also significantly lower than the predicted values.

Table 5.2.1: Stock Quantity and Profits in Experiment r1b

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	Predicted	p value	Data	Predicted	p value	Data	Predicted	p value
Mean	108	*124*		4978	*6970*		11224	*12986*	
Median	105	*124*	0.002	4824	*6830*	0.000	10536	*13067*	0.002
St. Dev.	21	*4*		2204	*513*		2237	*327*	

Next, we study the subject-level results to gain a more detailed understanding

Table 5.2.2 presents the results by manufacturer-retailer pairs. We observe heterogeneous behavior: Four retailers significantly understock, whereas three retailers overstocked, two significantly. Hence, one should be cautious in using average results to describe subject behavior.

Table 5.2.2.(a)-(c) Stock Quantity Decisions and Firms' Profits in Experiment r1b

Stock Quantity	**Ret 1**	**Ret 2**	**Ret 3**	**Ret 4**	**Ret 5**	**Ret 6**	**Ret 7**
Mean Data	138	131	112	121	135	100	107
Median Data	140	129	113	120	140	110	120
Pred. Q(w,r)*	*156*	*91*	*151*	*100*	*125*	*127*	*137*
p value	**0.049**	**0.000**	**0.000**	**0.000**	0.241	**0.000**	**0.001**

Retailer Profit	**Ret 1**	**Ret 2**	**Ret 3**	**Ret 4**	**Ret 5**	**Ret 6**	**Ret 7**
Mean Data	9269	3036	5654	3634	3848	6895	8101
Median Data	10450	4635	5920	7000	3800	5050	9050
Stdev	6361	6647	3029	6575	4687	5646	5425
Pred. Profit	*10765*	*3315*	*7000*	*4963*	*4921*	*8827*	*9171*
p value	0.597	0.304	0.090	0.139	0.230	0.472	1.000

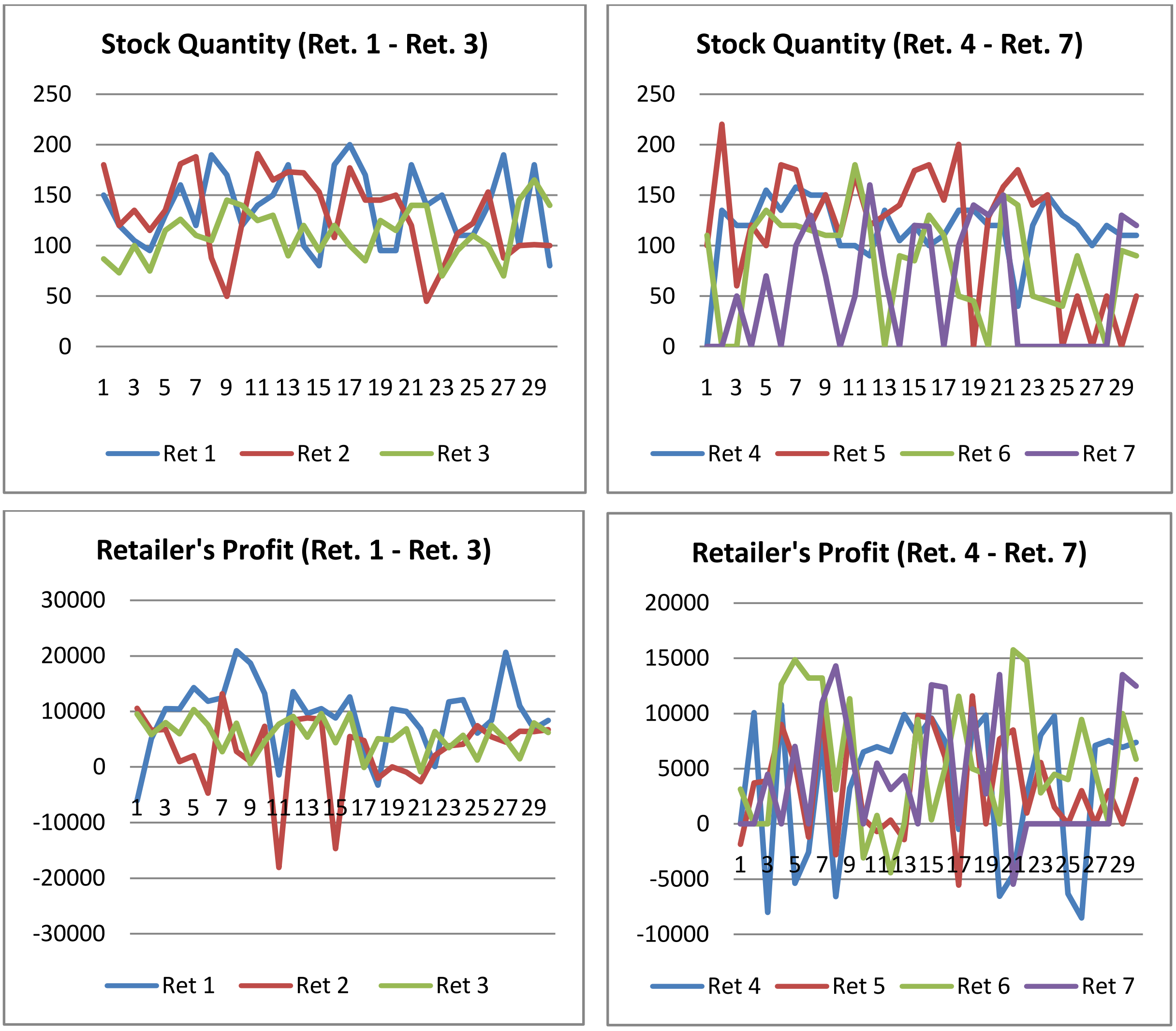
Mfg. Profit	Mfg 1	Mfg 2	Mfg 3	Mfg 4	Mfg 5	Mfg 6	Mfg 7
Mean Data	10153	18041	11303	14516	14441	9105	9418
Median Data	9500	17240	11950	14400	13230	9920	10241
Stdev	3039	5353	3016	2820	6062	3305	2740
Pred. Profit	*11558*	*12879*	*14836*	*12725*	*15067*	*11703*	*11997*
p value	**0.004**	**0.000**	**0.000**	**0.000**	0.415	**0.000**	**0.002**

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 revenue share term: 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 5.2.2(a)-(f) presents the stock quantities and profit levels for the seven pairs separately over time. 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-6) 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 2 and 4, ended up losing money in some games. Retailer-2 made loss in six games, averaging $7,170. Retailer-4 made loss in nine games, averaging $5,443. These losses explain the difference between Retailer 2 and 4’s mean and median profit levels. Pair-2 is worth analyzed. It seems that manufacturer offers contract parameters that give much of the profit to himself. Retailer-2 orders reasonable stock quantity as a reply that results high profits to manufacturer and low (sometimes negative) profit to Retailer-2. The situation with Retailer-1 is rather different. This retailer was offered very attractive contract terms, ordered high quantities, and made high profits without much risk. Her partner, manufacturer-1, paid the price of offering generous contract terms 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.

5.2.2 Manufacturer's Contract Parameter Decisions

Here we study the manufacturer's contract parameter *(w, r)* 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 5.2.3 (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.



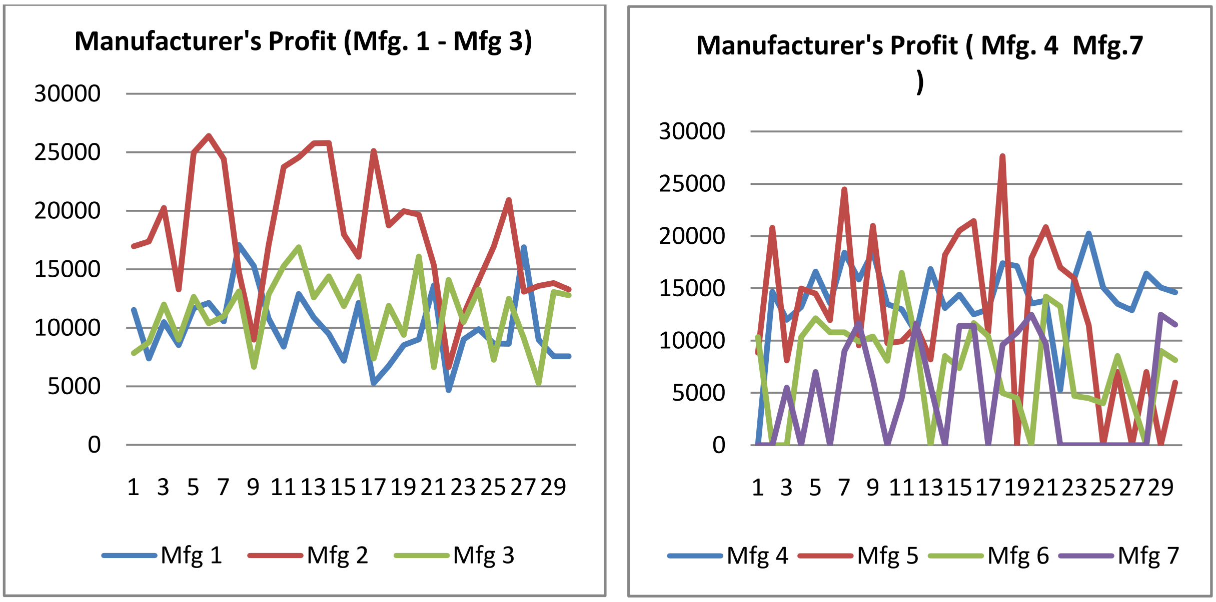


Figure 5.2.2 (a)-(f) Stock Quantities and Profit Levels for the Seven Pairs in Experiment r1b

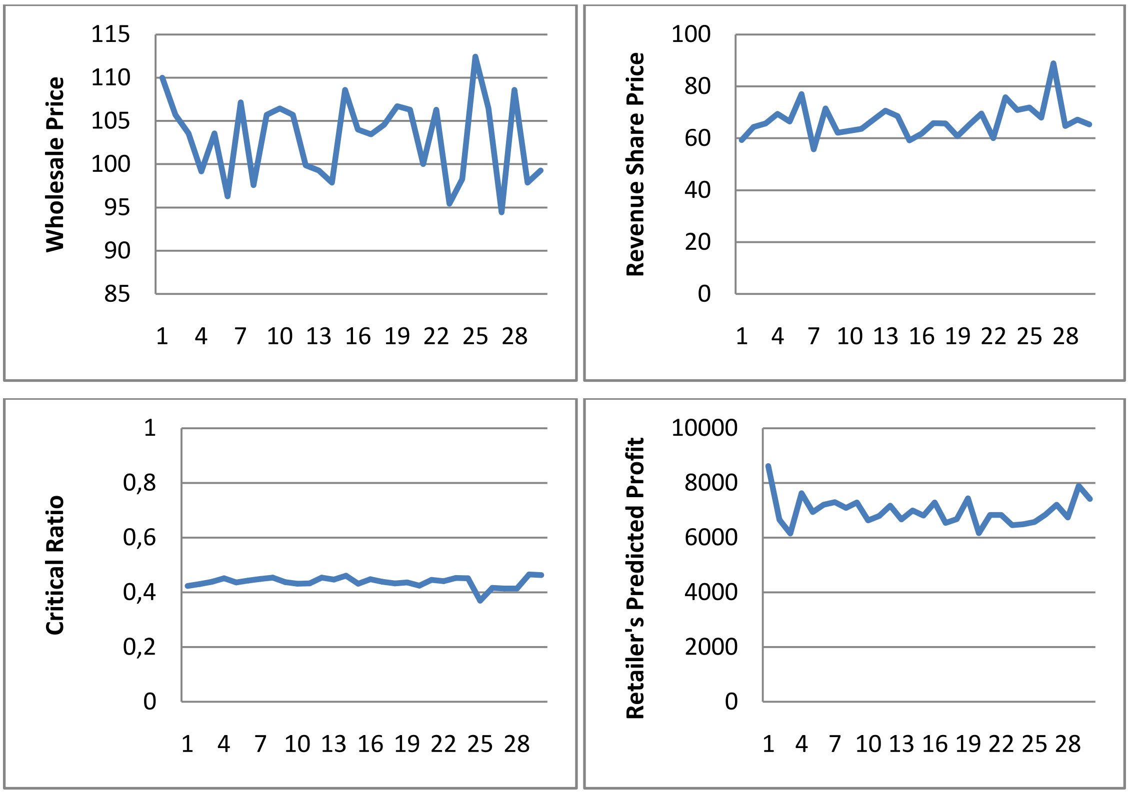


Figure 5.2.3 (a)-(d) Contract Parameters, Critical Ratio and Retailer’s Predicted Profit in Experiment r1b

Table 5.2.3: Contract Parameters in Experiment r1b

	Wholesale Price	**Revenue Share Price**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	1	246	0.75	*333*
Mean Data	103	67	0.44	*6971*
Median Data	104	66	0.44	*6830*
Stdev Data	4,7	6,38	0.01	*514*

We observe that on average, the manufactures choose much higher wholesale prices and much lower revenue share 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 r1b

	Mfg. Optimal	**Mfg.-1**	**Mfg.-2**	**Mfg.-3**	**Mfg.-4**	**Mfg.-5**	**Mfg.-6**	**Mfg.-7**
Wholesale Price w	1	69	145	56	149	75	124	105
Revenue Share Price r	246	74	51	120	29	114	23	60

Figure 5.2.4(a)-(b) below illustrates the retailer's expected profit (i.e., contract attractiveness) over time for all seven pairs. We observe that Manufacturer-1 offered very attractive contract terms, which lead to high stock quantities and high profits for Retailer-1. Due to the high wholesale price and revenue share price setting of Manufacturer-2, predicted profit of Retailer-2 is quite low. Retailer-7's predicted profit jumps up and down, due to changes in manufacturer's contract parameter decisions.

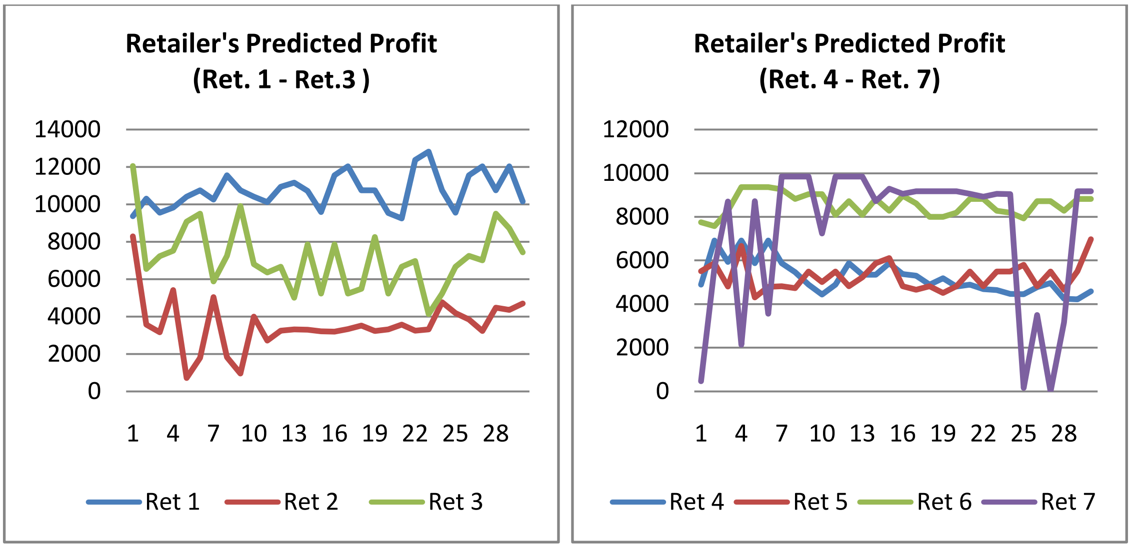


Figure 5.2.4. (a)-(b) Retailer's Expected Profit in Experiment r1b

Why did the manufacturers not offer their theoretical optimal contract, but offered much higher wholesale price and much lower revenue share 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 with 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 weight 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 ten games out of 180, (a retailer that rejects 12 contracts out of 30 period game is excluded) the fear of rejection is likely to keep the manufacturer from offering unattractive contracts.

5.2.3 Changes in Decisions over Time

Next, we aim to understand if and how the subjects' decisions change 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 r1b

	Stock Quantity			**Retailer Profit**			**Mfg. Profit**			**Wholesale Price**		**Revenue Share**		**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	110	111	*124*	5513	5064	7143	11532	11240	12810	104	105	66	65	0.44	0.44
10-20	119	120	*125*	4721	4825	6848	12540	12883	13070	104	105	65	66	0.44	0.44
21-30	95	94	*123*	4701	4633	6922	9600	9888	13080	102	100	71	69	0.44	0.44
p value	0.125			0.360			0.123			0.980		0.432		0.995	

We observe that overall, subjects do not seem to learn from experience. There is no consistent improvement in profits from the initial periods to the final ones. In fact, both retailer and manufacturer profits seem to decrease.

Next we look into the subject-level results given in 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 r1b

	Period	Pair-1	Pair-2	Pair-3	Pair-4	Pair-5	Pair-6
Q	**1-10**	144	110	130	120	130	127
	11-20	139	158	111	117	155	90
	21-30	138	102	118	112	104	76
	p-value	0.969	0.069	0.623	0.130	0.464	0.060
Retailer Profit	**1-10**	11137	4645	6316	2277	3624	6471
	11-20	7380	47	6251	4800	4577	7366
	21-30	9204	4417	4394	3849	3375	6449
	p-value	0.212	0.969	0.186	0.791	0.961	0.885
Mfg. Profit	**1-10**	11563	18461	10430	14933	14402	10929
	11-20	9071	21758	13024	14251	16698	8434
	21-30	9572	13904	10456	14346	10911	7042
	p-value	0.121	**0.045**	0.791	0.850	0.406	0.112
Retailer Predicted Profit	**1-10**	10332	3485	8182	5814	5207	8888
	11-20	10725	3240	6322	5290	5219	8488
	21-30	11139	3973	6964	4560	4790	7626
	p-value	0.140	0.405	0.212	**0.003**	0.405	0.121
w	**1-10**	78	149	62	144	79	120
	11-20	67	148	55	149	72	127
	21-30	60	143	49	152	67	111
	p-value	0.053	0.496	0.130	**0.003**	0.273	0.256
r	**1-10**	65	51	104	27	109	25
	11-20	75	51	127	27	116	21
	21-30	81	50	130	32	104	19
	p-value	0.082	0.520	**0.003**	0.112	0.344	0.623

Pair-1, Pair-2, Pair-5 and Pair-6 do not seem to learn from experience. Retailer's predicted profit decreased over time in Pair-4, since manufacturer increased wholesale price through the end of the game. Manufacturer-3 increased the revenue share price over time, but this does not affect retailer's profit significantly because the wholesale price is decreased as well.

5.2.4 Rejected Contracts

There are twenty four games (out of 210) where the retailers rejected the contract by setting zero stock quantity. Fourteen of the rejected contracts are from one single retailer, Retailer-7.Table 5.2.7 provides the details.

Table 5.2.7.Rejected Contracts with Predicted Results in Experiment r1b

Period of Rejection	Retailer Number	w	r	Q*	*Mfg's Predicted Profit*	*Retailer's Predicted Profit*
1	4	150	30	101	12,767	4,892
19	5	100	90	112	14,362	4,519
25	5	40	150	154	16,412	5,808
27	5	50	140	144	16,135	5,495
29	5	100	80	118	14,072	5,517
2	6	130	125	121	12,197	7,583
3	6	120	30	127	12,044	8,291
13	6	130	20	123	11,899	8,102
20	6	125	25	125	11,972	8,195
28	6	120	30	127	12,044	8,291
1	7	120	120	55	10,305	468
2	7	90	90	124	14,359	5,690
4	7	60	160	104	15,860	2,140
6	7	100	100	104	14,434	3,567
10	7	120	40	122	12,655	7,239
14	7	100	50	135	12,307	8,725
17	7	100	47	137	12,076	9,059
22	7	101	47	136	12,143	8,923
23	7	100	47	137	12,076	9,059
24	7	100	46	137	11,997	9,035
25	7	200	46	44	8,568	165
26	7	150	46	91	12,872	3,498
27	7	100	150	40	8,000	0
28	7	150	50	88	12,823	3,169

Retailers are more likely to reject contracts that provide them low predicted profit, 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. In particular, Retailer-7 rejected quite generous contracts. Risk aversion may explain this behavior. Although the contract provides positive expected profit, losses are also possible which causes risk for the retailer.

5.3. Experiment r2b Results (Short-run Interaction)

Experiment r2b is one of the short-run interaction experiments under revenue sharing contract. It has six manufacturer-retailer pairs. Contract rejection is observed in only 1 game.

5.3.1 Retailer's Stock Quantity Decision and Firms' Profits

Figure 5.3.1 (a)-(c) present the mean stock quantity and the firms' profits across six games over 30 periods.Table 5.3.1 summarizes the comparison.

We observe that retailers on average stocked lower than the predicted quantities, which is consistent with Experiment r1b. However, the difference between data and predicted values is quite small compared to Experiment r1b. We cannot speak of a significant understocking in this experiment. However, we observe from Figure 5.3.1(a) that the retailers understocked in the initial periods, but overstocked in the latter ones.

With these stock quantities, retailers obtained 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. However, in latter periods manufacturers' profit increases towards to the optimal value. This is because the manufacturers start offering less attractive contracts, but retailers keep increasing their stock quantity.

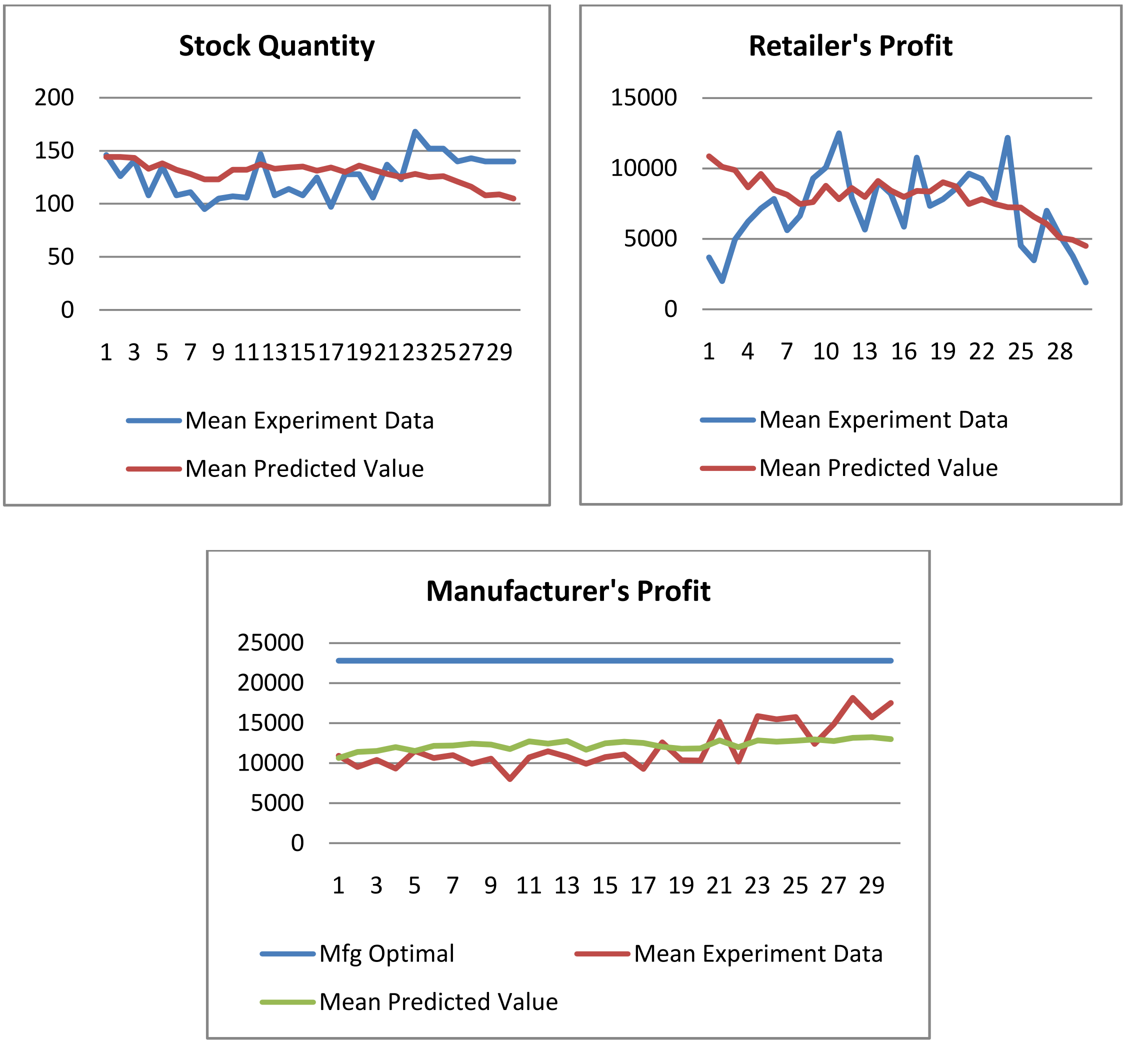


Figure 5.3.1 (a)-(c) Stock Quantity and Firms Profits in Experiment r2b

Table 5.3.1: Stock Quantity and Profits in Experiment r2b

	Stock Quantity			Retailer's Profit			Manufacturer's Profit		
	Data	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**	**Data**	***Predicted***	**p-value**
Mean	126	*129*		7073	*7948*		12013	*13322*	
Median	124	*132*	0.069	7263	*8062*	0.259	10861	*12462*	0.061
St.dev.	23	*10*		2707	*1458*		2702	*609*	

5.3.2 Manufacturer's Contract Parameter Decisions

Figure 5.3.2(a)-(d) illustrates the mean values of manufacturer's contract parameters, implied critical ratio and retailer's predicted profit. Table 5.3.2 summarizes the results.

We observe that the wholesale price is overall stable over time. The revenue share, however, has increase significantly over time, leading to a decrease in the retailer's predicted profit. On average, the manufactures choose higher wholesale prices and much lower revenue share prices than the optimal values. This is similar to Experiment r1b. 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 although the manufacturers reduce the attractiveness of the contracts over time, the contracts are still much more attractive than the ones in the optimal solution. This leads to a more equitable sharing of profits between the firms.

Table 5.3.2: Contract Parameters in Experiment r2b

	Wholesale Price (Data)	**Revenue Share Price (Data)**	**Critical Ratio**	***Retailer's Predicted Profit***
Mfg. Optimal	1	246	0.75	*333*
Mean	104	57	0.46	*7948*
Median	104	56	0.48	*8062*
Stdev	8	12	0.05	*1458*

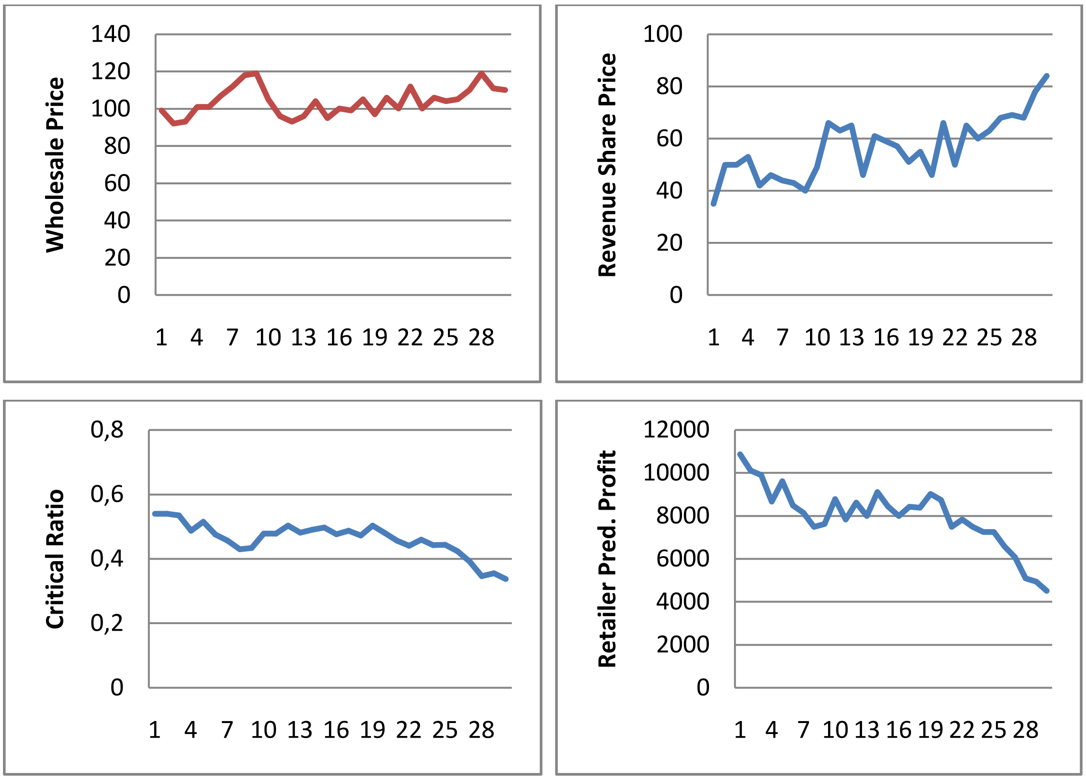


Figure 5.3.2 (a)-(d) Contract Parameters, Critical Ratio and Retailer's Predicted Profit in Experiment r2b

5.3.3 Changes in Decisions over Time

Here we aim to understand if the subjects' decisions change over periods. In Table 5.3.3, 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 5.3.3 Mean Values in Three Period Blocks in Experiment r2b

	Stock Quantity		Retailer Profit		Mfg. Profit		w	r	Critical Ratio
	Data	***Pred.***	***Data***	***Pred.***	***Data***	***Pred.***	**Data**	**Data**	**Data**
Per. 1-10	119	*134*	7425	*8960*	10183	*11806*	105	45	0.49
Per. 11-20	117	*134*	6410	*8444*	10731	*12311*	100	57	0.49
Per. 21-30	144	*120*	6584	*6441*	15126	*12850*	108	67	0.41
p-value	**0.001**		0.676		**0.000**		0.171	0.238	**0.000**

We observe that the retailers understocked in the initial periods leading to quite poor profits. In the last periods, the retailers overstocked on average. However, this benefited the manufacturers as attractiveness of the contracts also decreased.

We observe no significant change in wholesale price, revenue share price, and retailer profit 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 decrease in retailer's predicted profit indicates that the manufacturer offers more aggressive contract terms in the last periods.

5.3.4 Rejected Contracts

The following table summarizes the data of the game in which the retailer rejected the contract. The rejection is likely to be caused by the relatively low profit share of the retailer.

Table 5.3.4 Rejected Contracts with Predicted Results in Experiment r2b

Period of Rejection	Retailer Number	w	r	Q*	*Mfg's Predicted Profit*	*Retailer's Predicted Profit*
5	8	190	0	86	*11,984*	*3,745*

We observe that rejection rate is lower in short run experiments than long run experiments. This may be due to the one short interaction logic, retailers do not want to sacrifice any profit by rejecting a contract that is proposed by an unknown manufacturer. In the long-run experiments, the retailer may reject a contract with the hope of receiving more favorable contracts in subsequent periods. In short-run interactions, there is no such motive because the pairs keep changing every period.

CHAPTER 6

6. FEATURE SELECTION AND CLASSIFICATION

So far, we have observed that the retailers deviate from the optimal newsvendor stock quantity decision. In this chapter, we aim to understand the factors that affect retailer's decision. We use the data of buyback contract short-run experiments, namely b2a and b2b which contain 16 manufacturer-retailer pairs. Recall that these experiments were conducted previously and reported in Sahin and Kaya (2011). We use subject-level data because averages may be misleading. First, to identify the most important factors, we apply "feature selection" methodology to data. Then, we build regression models to capture the relationship between the stock quantity decisions and the selected attributes.

6.1. Feature Selection

Feature selection is the process of selecting a subset of relevant features to use in model construction. Feature selection has been an active research area in statistics and data mining. The central assumption when using a feature selection technique is that the data contains many redundant or irrelevant features. The objective of feature selection is three-fold: Improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data (Guyon and Elisseeff 2003).

We apply feature selection to each individual retailer's quantity decisions, and try to figure out which attributes are effective the decision making process. We use the machine learning software Weka, which contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality. We chose the stock quantity as the “output”, and nine “attributes” that can potentially affect the stock quantity decision as shown in Table 6.1.1

Table 6.1.1 Output Variable and Attributes

Output	Attribute No	Attribute Name	Abbreviation
Stock Quantity	1	Period	period
	2	Cost of Underage	cu
	3	Cost Of Overage	co
	4	Manufacturer Realized Profit	mfgd
	5	Manufacturer Expected Profit	mfge
	6	Past Demand Realization	pdr
	7	Retailer Realized Profit	rd
	8	Retailer Expected Profit	re
	9	Retailer Profit Share	profitshare

Period refers to the phases of 30 period decisions. We assign number 1 for the first ten periods’ decision, 2 for the next ten periods’ decision, and 3 for the last ten periods. Past demand realization, Manufacturer realized profit and Retailer realized profit and Retailer’s profit share refer to the relevant values in the previous period. Manufacturer expected profit and Retailer expected profit are the expected gains of the players in the current round given the stock quantity. Cost of underage and overage are used instead of the contract parameters wholesale price and buyback price. To avoid collinearity, we chose not to use total profit (sum of manufacturer and retailer profit), and critical fractile (because it is a linear function of contract parameters w and b).

In Weka software, RelieffAttributeEval was used with the ranker search method. RelieffAttributeEval method evaluates the value of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. This method operates on both discrete and continuous class data. In ranker method, all attributes are ranked starting from the most important one to the least important one. Cross validation is selected as the Attribute Selection Method.
We applied the same method to all 16 retailer’s decisions and we recorded each retailer’s five most important features. We assign weights to the attributes such as 5 if

the attribute is the most important one and 1 if it is the last one important. Then, we calculated each attribute's weighted sum, and we rank the first five attributes that are most effective in making decisions. The results are shown in Table 6.1.2 and Table 6.1.3.

Table 6.1.2: The Most Important 5 Attributes Selected by b2b Retailers

Experiment	Retailer	Selected Att. 1	Selected Att. 2	Selected Att. 3	Selected Att. 4	Selected Att. 5
b2b	8	co	mfge	rd	period	profitshare
b2b	9	co	cu	re	mfge	period
b2b	10	co	mfge	re	period	pdr
b2b	11	co	re	cu	mfge	mfgd
b2b	12	period	co	mfge	mfgd	profitshare
b2b	14	co	mfge	re	cu	profitshare
b2b	15	co	mfge	re	cu	pdr

Table 6.1.3: The Most Important 5 Attributes Selected by b2a Retailers

Experiment	Retailer	Selected Att. 1	Selected Att. 2	Selected Att. 3	Selected Att. 4	Selected Att. 5
b2a	8	mfgd	period	pdr	co	profitshare
b2a	9	co	re	cu	mfge	profitshare
b2a	10	co	re	cu	pdr	mfge
b2a	11	mfgd	pdr	rd	profitshare	cu
b2a	12	co	profitshare	mfge	re	cu
b2a	13	mfgd	period	pdr	co	profitshare
b2a	14	co	mfgd	re	pdr	mfge

Table 6.1.4 Weighted Sum of Each Attribute in Experiments b2b and b2a

Experiment	Attribute	Weighed Sum	Experiment	Attribute	Weighed Sum
b2b	co	34	b2a	co	29
b2b	mfge	23	b2a	mfgd	19
b2b	re	16	b2a	re	17
b2b	cu	11	b2a	pdr	14
b2b	period	10	b2a	mfge	10
b2b	rd	3	b2a	cu	10
b2b	profitshare	3	b2a	profitshare	9
b2b	mfgd	3	b2a	period	8
b2b	pdr	2	b2a	rd	4

Weighted sum of each Selected Attribute in the two experiments are shown in Table 6.1.4. For Experiment b2b we see that cost of overage is the most important attribute that affects the retailer decision. The other important attributes include Manufacturer's expected profit, Retailer's expected profit, Cost of underage and Period. As illustrated in the table, four of the top five attributes for experiment b2a are similar to the ones found in the top five of experiment b2b.

The reason why cost of overage is the most important attribute in both experiments might be risk aversion of the retailer. Buyback price is generally far less than the wholesale price in proposed contracts. Because demand is probabilistic, retailers avoid taking high risk and hence, cost of overage becomes the most important factor affecting their stock quantity decision. Expected profits of both sides might be important due to the fairness concerns. If manufacturer's expected profit is much higher in a given contract, retailer will not be willing to order high quantities. We observe that cost of underage is also important but not as much as the cost of overage.

6.2. **Classification**

The next step after feature selection is classification. Classification takes a data set with known output values and uses this data set to build a model. We apply linear regression to classify the data in Minitab software. The output is retailer's order quantity decision, and the selected five attributes are the independent variables of the regression model. We hope to build more accurate regression models as we exclude the redundant attributes identified in the feature selection phase.

Recall that selected five attributes for Experiment b2b are cost of overage, manufacturer's expected profit, retailer's expected profit, cost of underage and period. We expect stock quantity to be increasing in the retailer's expected profit, cost of underage and period; and decreasing in the cost of overage and manufacturer's expected profit attributes. We expect stock quantity to be increasing with the period due to the learning effect. We expect decision makers to understand the logic of the game, and start ordering higher stock quantities. Minitab results for each individual retailer are shown below in Table 6.2.1.

Table 6.2.1 Regression Equations for Each Retailer in Experiment b2b

Retailer	R^2	Adjusted R^2	p value	Regression Equation
1	0.528	0.415	**0.005**	Q = 294 – **1.38 co** – 0.00158 mfge – 0.0147 re + 1.55 cu – 12.9 p
2	0.708	0.644	**0.000**	Q = - 487 + 0.989 co **+ 0.0337 mfge + 0.0486 re** – 2.62 cu – 9.84 p
3	0.480	0.367	**0.007**	Q = - 79 + 0.35 co + 0.0086 mfge + 0.0531 re – 3.68 cu – 3.4 p
4	0.549	0.450	**0.002**	Q = - 794 + **2.49 co + 0.0442 mfge + 0.102 re – 7.33 cu** – 3.84 p
5	0.366	0.229	**0.049**	Q = - 795 + 2.06 co + **0.0411 mfge** + 0.0704 re – 4.50 cu + **22.4 p**
7	0.822	0.783	**0.000**	Q = 97 – 0.028 co + 0.0022 mfge + 0.0348 re – **3.15 cu** + 6.29 p
8	0.543	0.444	**0.002**	Q = - 263 + 1.64 co + 0.0150 mfge **+ 0.0865 re – 7.45 cu** + 9.03 p

The regression equations are significant and R-squared values seem high. However, most of the factors in regression equations were not found to be significant even at 10% level. Significant factors in equations are shown with bold fonts in Table 6.2.1. The signs of the beta coefficients in regression equations usually follow our predictions. For example, cost of overage usually has a negative sign, whereas cost of underage has positive. Retailer’s expected profit has positive sign. Interestingly, manufacturer’s expected profit sign is also positive for most retailers. The retailers seem to care positively about the manufacturer’s profit as well.

Table 6.2.2. Regression Equation for Each Retailer in b2a Experiment

Retailer	R^2	Adjusted R^2	p value	Regression Equation
1	0.448	0.297	**0.028**	Q = 716 – 3.22 co – 0.00278 mfgd – 0.0914 re **+ 0.354 pdr + 8.42 cu** – 0.0242 mfge
2	0.853	0.812	**0.000**	Q = - 174 + 0.468 co – 0.00054 mfgd + 0.0417 re – 0.0303 pdr – 2.91 cu + 0.0167 mfge
3	0.846	0.804	**0.000**	Q = - 1141 **+ 3.07 co** + 0.00110 mfgd + **0.111 re** + 0.0359 pdr **– 7.50 cu + 0.0585 mfge**
4	0.690	0.605	**0.000**	Q = - 88 – 0.02 co **+ 0.00524 mfgd** – 0.0033 re **+ 0.154 pdr** + 1.11 cu + 0.0048 mfge
5	0.950	0.937	**0.000**	Q = - 384 + **1.10 co** – 0.000433 mfgd **+ 0.0597 re** – 0.0001 pdr **– 4.28 cu + 0.0263 mfge**
6	0.198	0.000	0.507	Q = 1175 – 3.41 co + 0.00117 mfgd – 0.106 re + 0.166 pdr + 7.79 cu – 0.0486 mfge
7	0.541	0.416	**0.005**	Q = - 1568 + 3.95 co – 0.00185 mfgd **+ 0.153 re** + 0.118 pdr **– 10.3 cu + 0.0819 mfge**
8	0.719	0.642	**0.000**	Q = 348 – 0.16 co + 0.00139 mfgd + 0.0125 re + 0.0418 pdr – 2.35 cu- 0.0081 mfge

Next, we develop regression models on “pooled” data for each experiment. We convert each retailer number into nominal value such as p1 for Retailer-1. Results are shown in Table 6.2.3.

Table 6.2.3 Regression Equations of Pooled Data for Each Experiment

Experiment	R^2	Adjusted R^2	p value	Regression Equation for each experiment
b2a	0.485	0.458	**0.000**	Q = 46.0 **– 0.402 co** + 0.000261 mfgd **+ 0.00625 re** + 0.00631 mfge – 0.30 p2 – 11.8 p3 + 9.20 p4 + 0.49 p5 – 14.4 p7 + 5.67 p8
b2b	0.425	0.394	**0.000**	Q = 186 **– 0.672 co** – 0.00105 mfge + 0.00016 re + 0.387 cu + 13.9 p2 – 15.0 p3 + 7.2 p4 **– 21.8 p5** – 17.5 p7 – 26.7 p8

In b2a experiment, the regression is significant but only the cost of overage and retailer’s expected profit are significantly important. None of the individual retailer variables were found to be significant. Similarly, in Experiment b2b, we obtain a significant regression, but only the cost of overage and Retailer-15 are the significant attributes.

Based on these observations, we conclude that although it is reasonable to apply regression, we could not find a strong evidence between the attributes and the stock quantity decision.

CHAPTER 7

7. FAIRNESS CONCERNS

Research in behavioral economics in the past two decades has shown that there is a significant incidence of cases in which firms, like individuals are motivated by concerns of fairness in business relationships, including channel relationships. Many studies have shown that fairness concern plays an important role in channel coordination. Manufacturers and retailers could forgo their profit margins when they care about fairness.

7.1. The Regression Model

To study whether our retailers decisions were affected by fairness concerns, we develop multiple linear regression models on Experiment b1a data, using SPSS v17 software. Pooling the order quantity decisions of all six retailers, and excluding rejected contracts we obtain n=171 data points. Stock quantity is the dependent variable, and the four variables listed in Table 7.1.1 are the independent variables.

Table 7.1.1: Regression Independent Variables and Descriptions

Name	Abbreviation	Description
D - Q	D-Q	Previous period absolute value of (demand - stock quantity)
Mfg profit previous	mfgp	Manufacturer's profit of previous period
Retailer profit previous	rp	Retailer's profit of previous period
Expected retailer mfg ratio	r/m	Profit ratio of manufacturer and retailer in current period

The fourth independent variable is our fairness measure. Descriptive statistics of the variables for 171 observations are shown in Table 7.1.2.

Table 7.1.2: Descriptive Statistics of Each Variable

Variable	**Mean**	**Std. Deviation**
Q	127	42
D - Q	58	40
Mfg profit previous	13,844	5,727
Retailer profit previous	5,213	6,658
Expected ret mfg ratio	0.497	0.445

We run multiple linear regression using SPSS 17.0 and we test the null hypothesis that claims there is no relationship between retailer's stock quantity decision and the independent variables. Results are shown in Table 7.1.3.

Table 7.1.3: Multiple Linear Regression Results

$\mathbf{R^2}$	**Adjusted $\mathbf{R^2}$**	**P value**	**Equation**
0.246	0.228	**0.000**	Q(t) = 59.218 + **0.167(D-Q) + 0.002(mfgp) + 0.001(rp) + 41.522(r/m)**

The F test p value shows that the regression equation is significant. The R-square value indicates that 24.6 % of the variability in the stock quantity decisions can be explained by the independent variables. All independent variables are statistically significant in explaining the deviations in dependent variable. We expect (D-Q)'s beta value to be positive; the increase in difference between demand and stock quantity decision should affect stock quantity decision positively. We expect retailer's previous period realized profit and retailer's profit share of the current period to affect stock quantity decision positively. We observe that the signs of the beta coefficients are all positive in our regression model, which is line with our expectations.

7.2. **Diagnostics and Remedial for Residuals**

There are three assumptions in multiple regression model. First, there must be a linear relationship between dependent variable and all independent variables. Second, the error term has constant variance with mean zero. Third, the error term is normally distributed. To test linearity and constant variance assumption of residuals, we look at the matrix plot of the dependent variable and all independent variables, residual plots against independent variables and partial residual plots. By looking at the residual plot against independent variables, we suspect that the linearity assumption holds only in retailer previous profit independent variable, and the constant variance assumption might be violated. To check constant variance assumption, we applied Modified Levene Test determine which independent variables to transform. Figure 7.2.1 shows matrix plot of dependent variable and Figure 7.2.2 shows unstandardized residual plot for the independent variable D-Q.

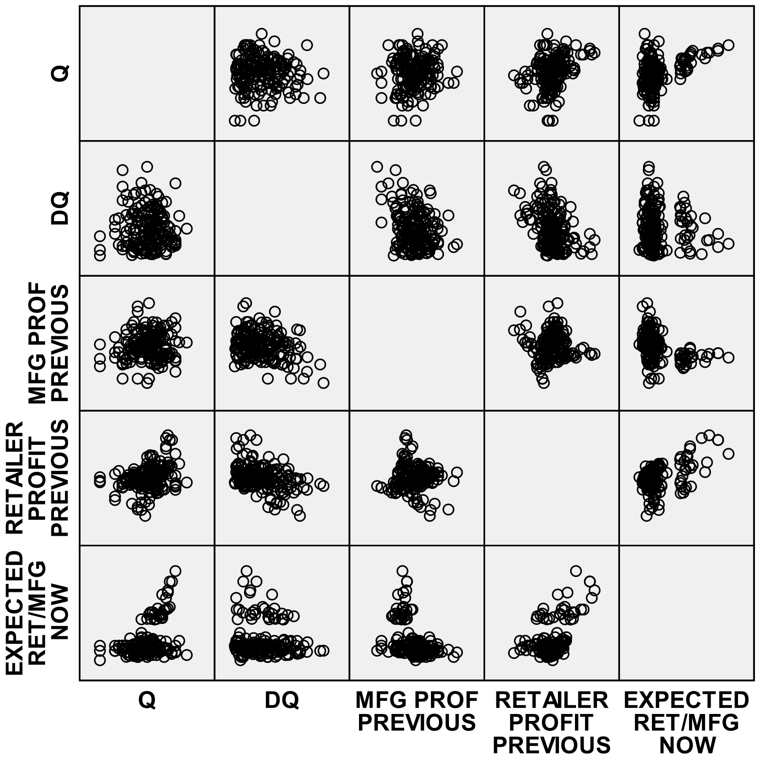


Figure 7.2.1: Matrix Plot of all Variables

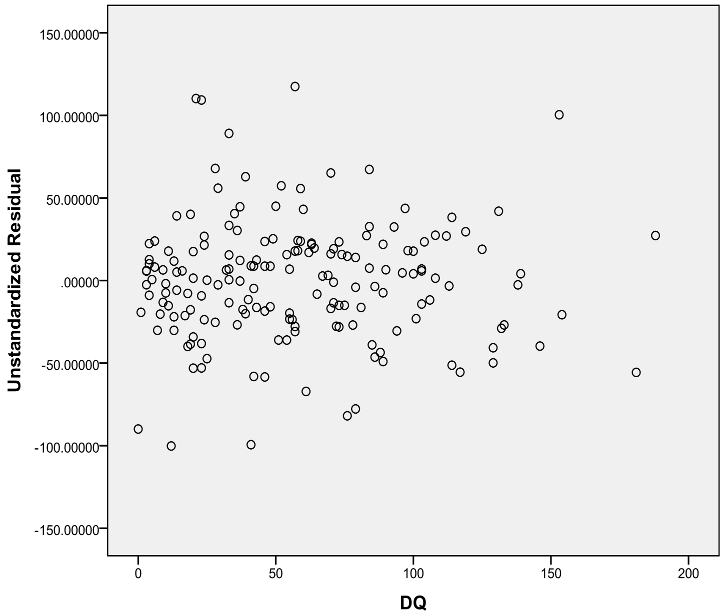
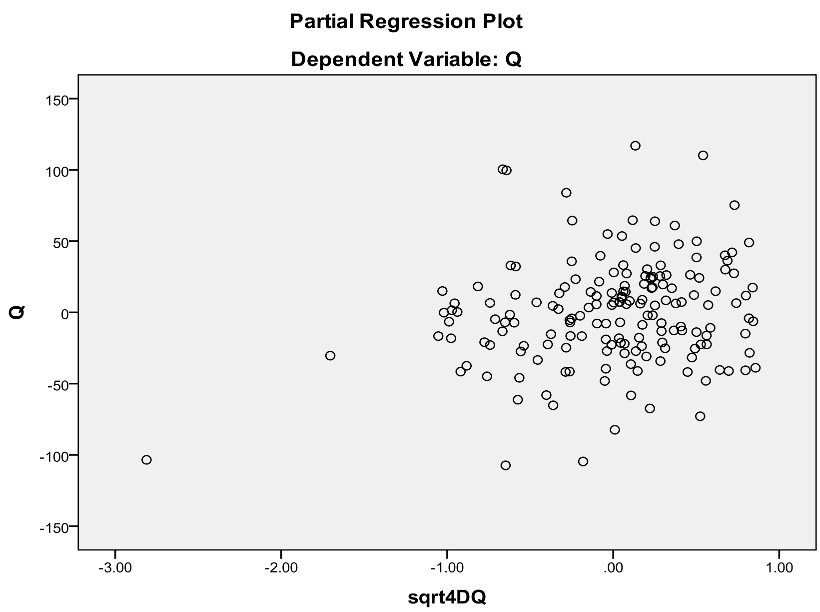


Figure 7.2.2: Unstandardized Residual plot for D-Q(t-1)

We observe that linearity assumption is violated in D-Q and r/m . Hence, we transform these independent variables with the fourth square root of each data point. Table 7.2.1 summarizes the change in R^2 values after two transformations. Figure 7.2.3 (a)-(b) show partial regression plots of transformed predictor variables after transformation.

Table 7.2.1: Transformed Predictor Variables and New R^2 Values

Transformed Pred. Variables	**Transformation**	**R^2**	**Adjusted R^2**
D-Q	$\sqrt[4]{\text{D-Q}}$	0.261	0.243
r/m	$\sqrt[4]{r/m}$	0.276	0.258



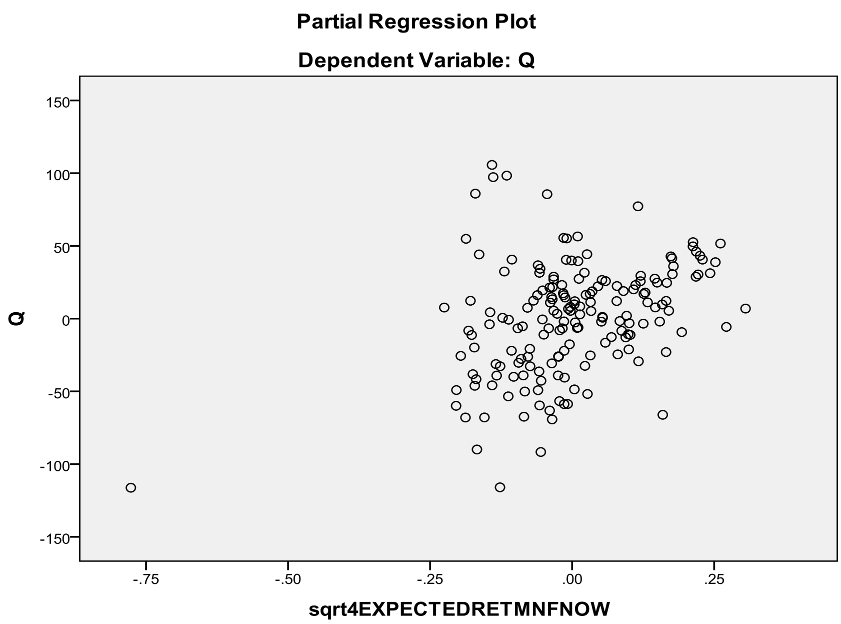


Figure 7.2.3: Partial Regression Plots of Predicted Variables after Transformation

We observe that linearity assumption holds after the transformations. We applied Modified Levene Test to check constant variance assumption and conclude that none of the independent variables violate constant variance assumption. The results of Modified Levene Test results are shown in Appendix D. The last assumption to check is the normality of the error term. By checking the histogram of the standardized residuals in Figure 7.2.4, we conclude that error term is normally distributed.

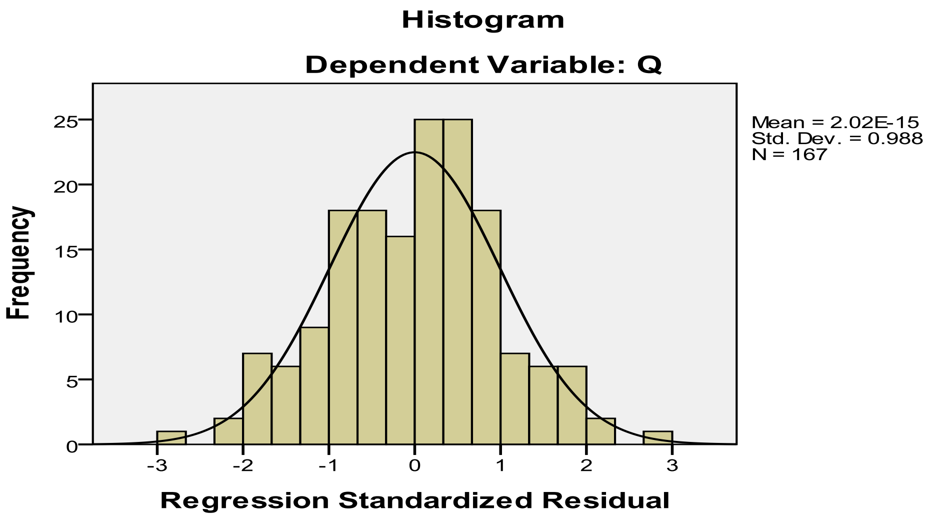


Figure 7.2.4 Histogram of Regression Standardized Residuals

We also test the normality of error terms through the Kolmogorov Smirnov test. As shown in Table 7.2.2 that normality assumption holds.

Table 7.2.2: The Results of the Kolmogorov Smirnov Test

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	.060	167	.200[*]	.995	167	.853

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

7.3. **Testing for Outliers**

Since outliers have crucial effects on the data and regression equation, we try to detect outlying independent (X) and dependent (Y) variable observations of the data. After detecting outlying data, we extract them from the model and rerun multiple linear regression.

The studentized deleted residual is the residual that would be obtained if the regression was re-run omitting that observation from the analysis. This is useful because some points are so influential that when they are included in the analysis they can pull the regression line close to that observation making it appear as though it is not an outlier, however when the observation is deleted, it then becomes more obvious how outlying it is. Studentized Deleted Residuals is used to identify cases with outlying Y observations. Decision rule of detecting a Y outlier is shown in Appendix E.Figure 7.3.1 shows Box plot of Y observations. Cases 15 , 26 , 150 , 166, 169 and 172 are found to be outliers and extracted them from the data.

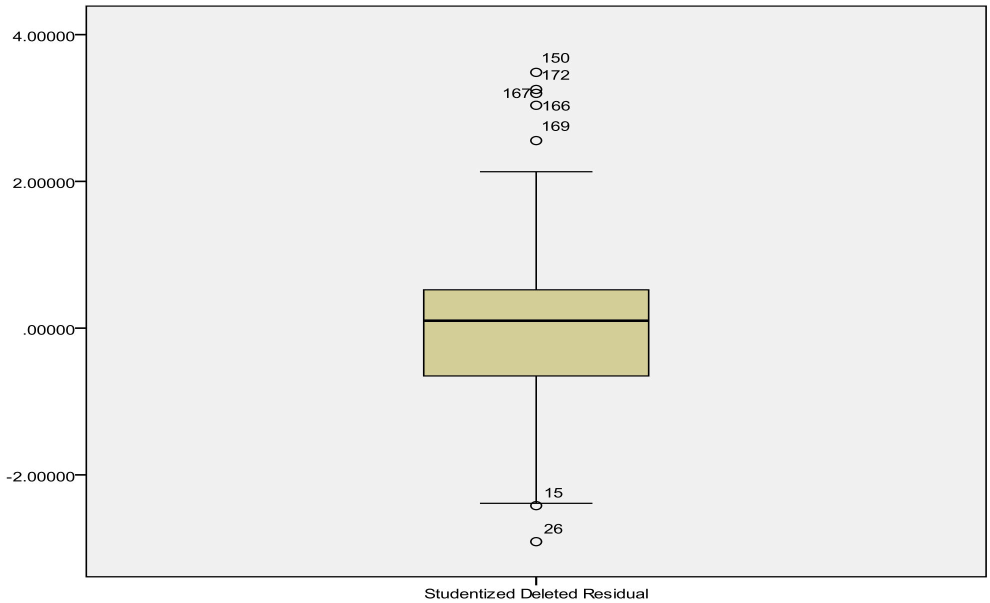


Figure 7.3.1: Box Plot for Extreme Y Values

Hat matrix leverage values (measures of the distance between the X values and the mean of the X values for all n cases) is used for identifying X outliers. Decision rule of detecting an X outlier is shown in Appendix E. Twelve X values are detected as outliers and extracted from the data. After extracting outliers from the data, we run another regression with the new data set. Table 7.3.1 summarizes the results of the new regression equation.

Table 7.3.1: Regression Results after Transformation and Extracting Outliers

R^2	Adjusted R^2	p value	Equation
0.662	0.438	**0.000**	Q(t) = -70.114 + 17.32Sqrt4(D-Q) + 0.003(mfgp) + 0.002(rp) + 128.636Sqrt4(r/m)

We check normality assumptions for residuals and multicollinearity in the new transformed regression model. Kolmogorov Smirnov test assures that normality assumption holds. Variance Inflation Factor is checked and no multicollinearity was detected.

We observe from the transformed equation that fairness concern is an important factor in retailer's stock quantity decision. In fact, a 2% increase in the fairness measure (the ratio of retailer's and manufacturer's expected profits) result in a 1.2% increase in the stock quantity decision.

CHAPTER 8

8. CONCLUSION AND FUTURE RESEARCH

In this thesis, we compare the experimental performances of three popular supply chain contracts (wholesale price, buyback and revenue sharing contracts). Revenue sharing contract experiments were conducted as part of this thesis work, whereas wholesale price and buyback contract experiment data are from Sahin and Kaya (2011).

We observe the decisions of both the retailer and the manufacturer players in experiments to deviate from the theoretical model's predictions. In particular, the manufacturers offered more "attractive" contracts than predicted, while the retailers chose suboptimal stocking quantities in response.

The simple wholesale price contract performed better than predicted in terms of total profits, contract efficiency and retailer profits. This is because the manufacturers offered more attractive contracts, and the retailers, on average, overstocked relative to theoretical prediction. The revenue sharing contract, on the other hand, performed significantly worse than predicted. In theory, the revenue sharing contract should have been equivalent to the buyback contract. In experiments, however the revenue sharing contract lead to lower manufacturer profits and total profits than the buyback contract. The retailer's profit, on the other hand, is higher. Interestingly, the offered revenue sharing contracts were more attractive than the buyback contracts, but the retailers somehow responded with lower stock quantities. The "framing difference" between the two contracts is likely to be the explanation. The retailers may prefer a buyback contract to an equivalent revenue sharing contract because the buyback contract emphasizes safety (manufacturer buying back unsold units), whereas the revenue sharing contract emphasizes share of sales revenue (some portion of revenue going to the manufacturer). Likewise, there was no significant difference between the attractiveness of the revenue sharing and wholesale price contracts, but the latter resulted in much higher manufacturer profits and total profits. These findings raise questions about the practical usefulness of the revenue sharing contracts.

For all contract types, we observe the manufacturers to offer more attractive contracts than predicted. Fairness concerns (see Bolton and Ockenfels 2000) of the subjects is likely to be an effective factor here. Recall that the manufacturer has the power to offer the contract terms, but the retailer has the power to reject the contract. This "ultimatum structure" (see Camerer 2003) causes the manufacturer to consider retailer's reaction. The fear of contract rejection is likely to cause the manufacturers to offer more fair contracts that offer more equitable sharing of expected profits than theoretical prediction. In fact, our multiple linear regression study show that the fairness factor is important in the retailer's stock quantity decision.

We also studied the effects of relationship length. We expected the manufacturers to offer more attractive contracts and retailers to stock higher quantities in long-run relationship (the same manufacturer-retailer pair in all periods) experiments than in the short-run relationship (manufacturer-retailer pairs re-determined in each period) experiments. Surprisingly, we observed the opposite. Manufacturers are likely to offer more attractive contracts in the short-run relationships because they fear that the "unknown" retailer they face may reject the contract. In the long-run relationships, the manufacturer learns about the limits of the retailer and can be more confident in offering in less attractive contracts. Likewise, long-run relationships encourage "gaming" between the firms. The retailers may reject contracts or set low stock quantity values to show to the manufacturers that they are tough players, hoping that they will receive more attractive contract offers in following periods. In the end, the manufacturers offered more attractive contracts, and the retailers responded with higher quantity values in the short run relationships. Although not significantly different, the total profits, manufacturer profits and retailer profits are also higher in the short run relationships.

We observe high individuality in the data. Human subjects' decisions in experiments exhibit wide variation. In particular, some subjects were understocking while some others were seriously overstocking within the same revenue sharing experiment session.

Similar to other works in literature (see the discussions in Bolton and Katok 2008, and Becker-Peth, Katok and Thonemann 2009), some 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.

We apply feature selection and classification techniques to the buyback contract experiments to figure out if subjects determine their stock quantity decision in the light of some attributes. Out of nine candidates, we determine the most important five attributes as cost of overage, manufacturer's expected profit, retailer's expected profit, cost of underage and period number. We then build a regression model separately for each individual where stock quantity is the dependent variable and these five attributes are the independent variables. While the regression equations are significant, R-squared values are acceptable, and beta coefficient have predicted signs, most of the attributes are not found to be significant for most individuals.

This work can be extended in a number of directions. One possibility is to conduct experiments on other supply chain contract types, such as quantity discount contract and rebate contract, and present a more complete comparison. Another important extension would be to develop behavioral models to explain the subject decisions observed in our experiments. One can create regression models that consider, for example, risk aversion, loss aversion, or bounded rationality of the subjects. Yet another possibility is to allow negotiations between the firms, rather than considering "take-it-or-leave-it" contracts.

Despite the presence of advanced IT systems, it is the human managers that make contractual decisions in companies. Hence, an understanding of human biases related to contracting decisions is valuable for practice. In this respect, this thesis makes a number of managerial contributions. First, the simple wholesale price contract performs as good as the buyback contract, and much better than the revenue sharing contract. Second, human beings seem to care not only about their expected profits, but also about how this expected profit is distributed, i.e., fairness. Third, short –run relationships between firms may be preferable to long-run ones, because long-run relationships can be damaged by strategic moves.

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APPENDICES

Appendix A Sample Main Script Code in Revenue Sharing Experiments

```
// Define Player List

   Players p1,p2,p3,p4;//,p5,p6,p7,p8,p9,p10,p11,p12,p13,p14,p15,p16,p17,p18;
   Integer nplayer = 4;        // number of players



// declare variables

        Script("c:\program files\hp mums\Scripts\revenuesharing\var-model.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\var-dummy.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\var-state.cfg");

// Set parameter value

        Script("c:\program files\hp mums\Scripts\revenuesharing\dat-parameter.dat");

// define inputs

        Script("c:\program files\hp mums\Scripts\revenuesharing\def-input.cfg");


// stage logon

        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-logon.cfg");

// game stages

        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-start.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-setgrid.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-predisplay.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-fetchdata.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-exchange.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-results.cfg");
        Script("c:\program files\hp mums\Scripts\revenuesharing\stage-periodend.cfg");

Stage writedb {

                // no db write statements in debug
                Script("c:\program files\hp mums\Scripts\revenuesharing\stage-dblog-period.cfg");

                if (stage=1)
```

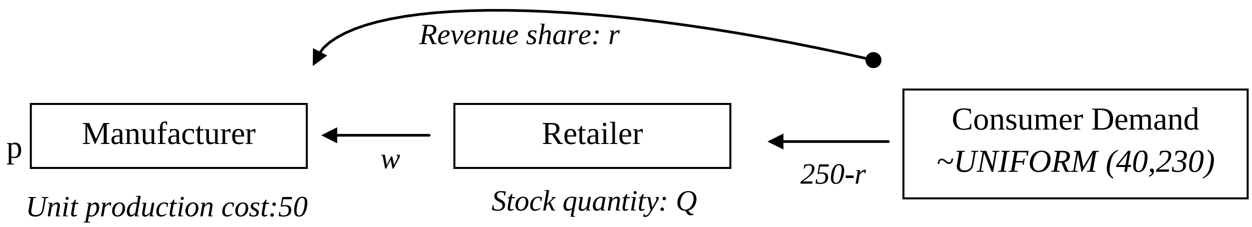
Appendix B Instructions for Revenue Sharing Contract Experiments with Short Run Relationship

Instructions for Revenue Sharing Contract Experiments

May/June 2013

<u>Scenario</u>

We consider a manufacturer who produces a certain product, and a retailer who buys the product from the manufacturer and sells it to consumers. Consumer demand is uncertain. It is a random number distributed uniformly *between 40 and 230*. That is, there is a 1/191 chance that demand will be equal to any of the integers between 40 and 230. The following figure illustrates the flow of money in the supply chain.



We consider a <u>three-stage</u> game between the manufacturer and the retailer:

<u>Stage-1:</u> The manufacturer determines the two contract parameters, and offers the contract to the retailer:

- ***Wholesale price, w***. This is the price at which the manufacturer sells his product to the retailer. The wholesale price has to be an integer less than the ***retail price 250***. Retail price is the price at which the retailer sells the product to consumers.
- ***Revenue share, r***: The manufacturer will receive a revenue share of r for each unit that the retailer sells to consumers. The retailer will keep the rest of the revenue, which is *250-r*. The amount *250-r* should be higher than the wholesale price *w*, otherwise the retailer will lose money for every unit sold. Hence, the manufacturer's revenue share r should satisfy $0 \le r \le 250 - w$.

<u>Stage-2:</u> The retailer observes the wholesale price and revenue share offers of the manufacturer, and determines his ***stock quantity, Q*** for the product. The retailer may

reject the manufacturer's offer by setting ***Q=0***. In this case, both firms earn zero profit. Otherwise, the retailer orders *Q* products from the manufacturer. The manufacturer produces this order by incurring the ***unit production cost 50*** per product, and delivers them to the retailer. The retailer stocks these products prior to the selling season. Because consumer demand can be between 40 and 230, the retailer's stock quantity *Q* decision also has to be between these values (if it is not equal to zero).

Stage-3: Random consumer demand is determined as "*d*". Using his stock of product, the retailer satisfies this demand as much as possible. The ***sales quantity*** of the retailer is the minimum of stock quantity and the realized demand. For each unit sold, the manufacturer gets *r* dollars and the retailer keeps *250-r*. Two cases are possible:

- If demand is higher than retailer's stock quantity (i.e., $d>Q$), then retailer will sell all *Q* units, and *(d-Q)* units of demand will be unsatisfied (***unsatisfied demand***).
- If demand is less than the retailer's stock quantity, (i.e., $d<Q$), then the retailer will sell *d* units, and *(Q-d)* products will be unsold (***leftover products***). These products have zero value.

Each firm aims to maximize its ***payoff*** (or, profit) in the game.

The retailer's payoff is calculated as the retail price times the sales quantity, minus the wholesale payment to the manufacturer, minus the manufacturer's revenue share payment.
That is, $\boldsymbol{250 * sales - w * Q - r * sales.}$

The manufacturer's payoff is calculated as the wholesale payment received from the retailer, minus the production cost, plus the revenue share payment from the retailer.
That is, $\boldsymbol{w * Q - 50 * Q + r * sales.}$

Note that there are three decisions in the game: The manufacturer determines the contract parameters *w* and *r* ; afterwards, the retailer determines his stock quantity *Q*. Both firms' decisions affect the payoff of both firms.

Preparation for Our Experiments

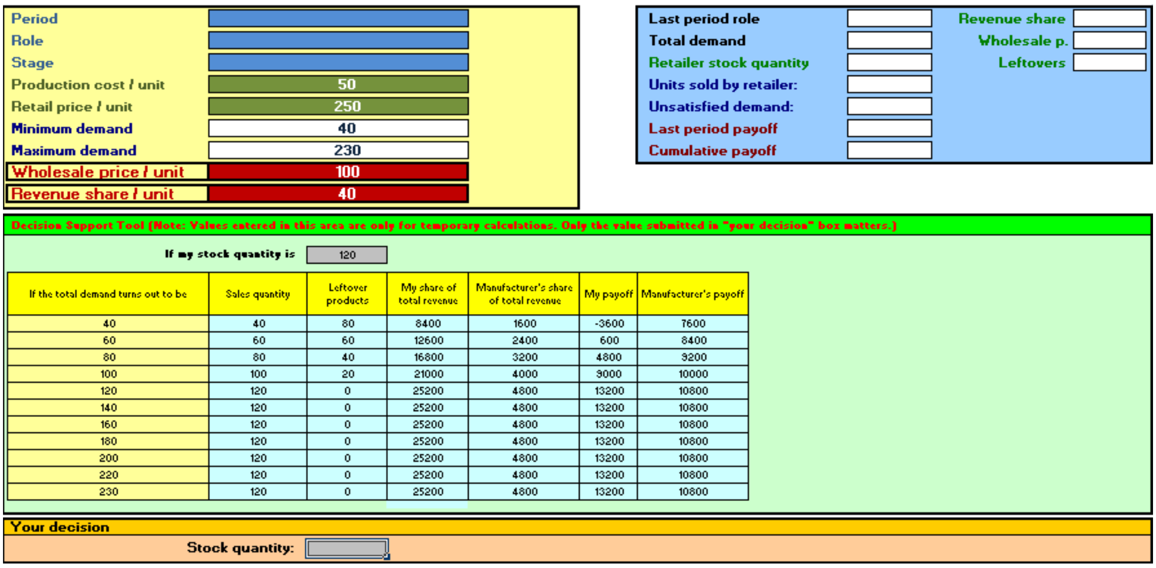
- The experiments will take place at the CAFÉ computer lab at the G-floor of the FMAN building.

- 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.

Our Experiment

- 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.
- The periods are independent of each other. A large or small demand realization in a period does not affect the demand in the later periods. Leftover products cannot be used to satisfy demand in following periods. Only your payoff will accumulate over time.

A Sample Screenshot: The following figure illustrates how the retailer's screen will look like at stage 2:



Period	
Role	
Stage	
Production cost / unit	50
Retail price / unit	250
Minimum demand	40
Maximum demand	230
Wholesale price / unit	100
Revenue share / unit	40

Last period role		Revenue share	
Total demand		Wholesale p.	
Retailer stock quantity		Leftovers	
Units sold by retailer:			
Unsatisfied demand:			
Last period payoff			
Cumulative payoff			

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 120

If the total demand turns out to be	Sales quantity	Leftover products	My share of total revenue	Manufacturer's share of total revenue	My payoff	Manufacturer's payoff
40	40	80	8400	1600	-3600	7600
60	60	60	12600	2400	600	8400
80	80	40	16800	3200	4800	9200
100	100	20	21000	4000	9000	10000
120	120	0	25200	4800	13200	10800
140	120	0	25200	4800	13200	10800
160	120	0	25200	4800	13200	10800
180	120	0	25200	4800	13200	10800
200	120	0	25200	4800	13200	10800
220	120	0	25200	4800	13200	10800
230	120	0	25200	4800	13200	10800

Your decision

Stock quantity:

Figure 0.1: Retailer's screen 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, the wholesale price and revenue share that the manufacturer set at stage 1.
- 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). Note that the submit button will be activated only after you enter a valid decision and hit enter (or, click somewhere in the screen). Invalid entries will cause warnings.
- The cells in which you can enter values are labeled with "gray" background.
- You can check the results of previous periods by clicking the ***Historical Results*** tab in the bottom of the screen. This will open a second worksheet with the titles seen below (for manufacturer):

Period	Role	Wholesale price	Mfg. revenue share	Retailer stock quantity	Customer demand	Sales quantity of the retailer	Leftover products	Unsatisfied demand	Payoff	Cumulative payoff

Figure 0.2: Historical results table (manufacturer)

<u>The Decision Support Tool</u>

Before you submit a decision, you can use the decision support tool that is in the middle of the screen. This tool allows you to calculate the outcome for certain values of your decision, the other firm'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 we record is the one you submit in the "stock quantity" box at the bottom of the screen.

<u>Retailer's decision support tool at stage-1</u>

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 summarizes the outcome for different consumer demand realizations (*d=40, 60, …, 230*) each in a row.

In the example in Figure 1, the retailer's stock quantity is entered as 120. We observe from the table that if consumer demand turns out to be, for example, 80, you (retailer) will sell 80 units because the demand is smaller than the stock quantity. Your leftover inventory will be 120-80=40 units. Since you satisfied all consumer demand, there will be no unsatisfied consumer demand. The manufacturer's share of the sales revenue will be 40*80=3200 dollars; whereas your share of the revenue will be (250-40)*80=16800 dollars.

Compare this with the outcome if consumer demand turns out to be 140. In this case, you (the retailer) will sell all of your 120 units, and there will be zero leftover inventory. Unsatisfied demand will be 140-120=20. The manufacturer's share of the sales revenue will be 40*120=4800 dollars; whereas your share of the revenue will be (250-40)*120=25200 dollars.

Manufacturer's decision support tool at stage-1

At stage-1, you (the manufacturer) will submit your wholesale price and revenue share decisions. However, in order to use the decision support tool, you also need to guess what stock quantity the retailer might determine at stage 2. Figure 3 below illustrates what the outcome will be if you set 100 as your wholesale price, 40 as your revenue share, and if the retailer sets 120 as his stock quantity (i.e., if he orders 120 products from you).

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

If my wholesale price is 100
and my revenue share is 40

and retailer's stock quantity is 120

If the total demand turns out to be	Retailer's sales quantity	Leftover products at the retailer	My share of sales revenue	Retailer's share of sales revenue	My payoff	Retailer's payoff
40	40	80	1600	8400	7600	-3600
60	60	60	2400	12600	8400	600
80	80	40	3200	16800	9200	4800
100	100	20	4000	21000	10000	9000
120	120	0	4800	25200	10800	13200
140	120	0	4800	25200	10800	13200
160	120	0	4800	25200	10800	13200
180	120	0	4800	25200	10800	13200
200	120	0	4800	25200	10800	13200
220	120	0	4800	25200	10800	13200
230	120	0	4800	25200	10800	13200

Your decisions

Wholesale price: **Revenue Share:**

Figure 0.3: Manufacturer's decision support tool at Stage 1.

Appendix C 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 Revenue Sharing Contracts

		With Null Orders					Without Null Orders				
		w	***r***	***Q***	***Mfg.Prof.***	***Ret.Prof.***	***w***	***r***	***Q***	***Mfg.Prof.***	***Ret.Prof.***
	Predicted	*1*	*246*	*183*	*22,784*	*333*	*1*	*246*	*183*	*22,784*	*333*
Exp.	**# of rej.**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**	**Data**
r1a	13	118	47	91	9,133	6,445	117	46	102	10,100	7,122
r1b	24	102	71	95	9,600	4,700	103	67	108	11,224	4,978
r2a	2	79	91	128	11,746	6,438	80	90	129	11,850	6,506
r2b	1	104	56	126	11,950	6,778	104	56	127	12,013	7,073

Appendix D Modified Levene Test Results

The steps of applied Modified Levene test is as follows:

- Partition the data roughly into two groups (1- 88 and 89 - 174).

- Obtain the residuals from the regression, and split the residuals of two groups. In this case, both groups have 87 observations.

- Obtain the median residual of each group

- Obtain the absolute deviation of each residual from its respective gropu median residual.

- Then, one tests the equality of the two means of the absolute deviation, by the standart t test for two independent means. If the two group mean absolute deviations are statistically unequal, then the residuals in one sside of the X range has larger variability than the other side.

- Hypothesis are:

  H_0 = Constant variance

  H_A = Not true

  Reject H_0 when p value < α.

  Modified Levene Test for X1, Sqrt4D-Q

Table 0.1Results of Modified Levene Test for transformed X1: SqrtD-Q

	Variable 1	*Variable 2*
Mean	25,99346861	27,68033
Variance	593,5766686	545,8681
Observations	87	87
Pooled Variance	569,7223705	
Hypothesized Mean Difference	0	
df	172	
t Stat	-0,46611473	
P(T<=t) one-tail	0,320861566	
t Critical one-tail	1,65376095	
P(T<=t) two-tail	0,641723133	
t Critical two-tail	1,97385213	

Since t Stat < t Critical two tail, we can not reject null hypothesis, constant variance assumption is not violated.

Table 0.2:Modified levene test for X2 : Manufacturer's previous realized Profit

	Variable 1	*Variable 2*
Mean	25,6629055	28,02395659
Variance	576,3682553	553,7694318
Observations	87	87
Pooled Variance	565,0688435	
Hypothesized Mean Difference	0	
df	172	
t Stat	-0,655087532	
P(T<=t) one-tail	0,256643273	
t Critical one-tail	1,65376095	
P(T<=t) two-tail	0,513286546	
t Critical two-tail	1,97385213	

Since t Stat < t Critical two tail, we can not reject null hypothesis, constant variance assumption is not violated.

Table 0.3:Results of Modified Levene Test for Retailers previous profit realization

	Variable 1	*Variable 2*
Mean	29,40327	24,26042

Variance	737,6114	389,7561
Observations	87	87
Pooled Variance	563,6838	
Hypothesized Mean Difference	0	
df	172	
t Stat	1,428668	
P(T<=t) one-tail	0,077457	
t Critical one-tail	1,653761	
P(T<=t) two-tail	0,154913	
t Critical two-tail	1,973852	

Since t Stat < t Critical two tail, we can not reject null hypothesis, constant variance assumption is not violated.

Table 0.4: Results of Modified Levene Test for SQRT4 fairness concern (expected ratio of retailer profit over manufacturer profit)

	Variable 1	*Variable 2*
Mean	26,7983549	26,87076
Variance	543,8146663	583,2371
Observations	87	87
Pooled Variance	563,5258775	
Hypothesized Mean Difference	0	
df	172	
t Stat	-0,020117492	
P(T<=t) one-tail	0,491986482	
t Critical one-tail	1,65376095	
P(T<=t) two-tail	0,983972964	
t Critical two-tail	1,97385213	

Since t Stat < t Critical two tail, we can not reject null hypothesis, constant variance assumption is not violated.

Appendix E Decision Rule for Detecting Outliers

Outlying Y observations

Studentized Deleted Residuals is used to identify cases with outlying observations.

Decision Rule:

Studentized Deleted Residual > t (1-α /2n ; n – p – 1) the case is outlier.

n : 174 , p = 5 α = 0.05

Studentized Deleted Residual > t (1- 0.05 / 348 ; 168) > t (0.0027 ; 168) = 3.15

Case 15 , 26 , 150 , 166, 169 and172 are outliers.

Outlying X observations

Hat matrix leverage values which are the measures of the distance between the X values and the mean of the X values for all n case is used for identifying X outliers.

Leverage values > 2p / n, the case is outlier.

2p / n = 0.05747   (see related excel sheet)

12 X values detected as outliers.