DECISION-MAKING EXPERIMENTS ON DUAL SALES CHANNEL COORDINATION

by
Ayşegül TİZER KARABAYIR

Submitted to the Graduate School of Engineering and Natural Sciences
in partial fulfillment of
the requirements for the degree of
Master of Science

Sabancı University
February, 2011

DECISION-MAKING EXPERIMENTS ON DUAL SALES CHANNEL COORDINATION

APPROVED BY:

Assist. Prof. Dr. Murat Kaya …………………………
(Thesis Supervisor)

Assoc. Prof. Dr. Can Akkan …………………………

Assist. Prof. Dr. Çağrı Haksöz …………………………

Prof. Dr. Gündüz Ulusoy …………………………

Assoc. Prof. Dr. Tonguç Ünlüyurt …………………………

DATE OF APPROVAL: ……………………………………………………..

# Acknowledgments

First, I would like to express my profound gratitude to my thesis adviser, Assistant Professor Murat Kaya for his invaluable guidance and useful suggestions throughout this research. His support, knowledge and motivation encouraged me to conduct my research with a high performance. I learned a lot from him during the thesis process.

I am gratefully thankful to my thesis committee for their valuable reviews, comments, and time spent on this thesis. I acknowledge the support of Fall 2010/2011 ENS 491 project groups 10 and 11 in conducting experiments. We are grateful for Fall 2010/2011 MS 454 students for acting as subjects in our decision-making experiments. We thank Sabancı University Faculty of Management for allowing us to use the CAFE (Center for Applied Finance Education) computer laboratory for our experiments. In particular, we are grateful to Mr. Oktay Dindar for his time and efforts. I would like to thank to my friends in the Industrial Engineering Graduate Program, in particular to Nükte Şahin for keeping me company through the research.

I want to give my deepest thanks to my parents and grandmother for their endless love, infinite support and trust throughout my life. My thanks go in particular to my brother Doğukan Tizer for his friendly support and motivation to complete this thesis.

Finally, I especially thank to my husband İrfan Karabayır for his endless love, great motivation, support and encouragement to apply and complete this program.

DECISION-MAKING EXPERIMENTS ON DUAL SALES CHANNEL COORDINATION

Ayşegül Tizer Karabayır

Industrial Engineering, Master of Science Thesis, 2011

Thesis Supervisor: Assist. Prof. Dr. Murat Kaya

Keywords: behavioral operations, buyback contract, coordination, direct channel, dual channels, experiments, retail channel, service-based competition, supply chain contracting, wholesale price contract

## Abstract

In this thesis, we conduct an experimental study with human decision makers, on dual sales channel coordination. We aim to determine dual channel strategies for a manufacturer who sells its product thorough both an independent retailer channel and its totally owned direct online channel. The two channels compete on service, where the service level of the retailer channel is measured with its product availability level, and the service level of the direct channel is measured with its delivery lead time. This multi-stage game-theoretical model was previously solved for the wholesale price contract (Chen et al. 2008) and buyback contract (Gökduman and Kaya 2009) cases. We compare these models' theoretical predictions with the outcome of our experiments with human decision makers. In particular, we analyze the theoretical and observed coordination performance of the wholesale price and buyback contracts between the two firms. We identify deviations from theoretical predictions that can be attributed to behavioral factors, such as risk aversion.

İKİLİ SATIŞ KANALLARININ KOORDİNASYONUNA İLİŞKİN KARAR-VERME DENEYLERİ

Ayşegül Tizer Karabayır

Endüstri Mühendisliği, Yüksek Lisans Tezi, 2011

Tez Danışmanı: Yrd. Doç. Dr. Murat Kaya

Anahtar Kelimeler: davranışsal operasyon, geri alım kontratı, koordinasyon, doğrudan kanal, ikili kanallar, deneyler, perakende kanalı, hizmet tabanlı rekabet, tedarik zinciri kontratları, toptan satış kontratı

## Özet

Bu tezde, insan karar vericilerle ikili satış kanallarının koordinasyonu üzerine deneysel bir çalışma gerçekleştirdik. Ürünlerini hem bağımsız bir perakendeci kanalı hem de kendisine ait doğrudan internet kanalı ile satan bir üretici için ikili kanal stratejileri belirlemeyi amaçladık. Kanallar arasında hizmet tabanlı bir rekabet varsayan modelimizde perakendecinin hizmet düzeyi ürün bulunabilirlik seviyesi ile belirlenirken üreticinin hizmet düzeyi ise müşteriye teslimat süresi ile ölçülmüştür. Bu çok aşamalı oyun teorisi modeli daha önce toptan satış kontratı (Chen et al. 2008) ve geri alım kontratı (Gökduman ve Kaya 2009) için çözülmüştür. Biz bu modellerin teorik tahminlerini insan karar vericiler ile yaptığımız deneylerin sonuçları ile kıyasladık. Özel olarak, iki şirket arasındaki toptan satış ve geri alım kontratlarının teorik ve gözlemlenen koordinasyon performanslarını analiz ettik. Teorik tahminler ve gözlemlenen veriler arasında riskten kaçınma gibi davranışsal faktörlerden kaynaklanabilecek sapmalar belirledik.

## Table of Contents

# List of Figures

# List of Tables

# CHAPTER 1

## CHAPTER 1 : INTRODUCTION

Technological improvements change many aspects of the human life. One effect of these improvements can be observed in the changing shopping behavior of consumers. Today most consumers prefer shopping from home via the Internet instead of going to a shopping mall and interacting with the products physically. As a result, sellers have been using the Internet (i.e., engage in e-commerce) as a sales channel. Forrester Research forecasts the increase of online retail sales in US from 2005 to 2010 as $157 billion, rate of e-commerce as 13% of US retail sales in 2010, and the European e-commerce amount as € 263 billion in 2011 (Forrester Resarch 2005, Yan 2008). Ease of selling via the Internet, the growing role of the Internet in human life, and economics of third party shipping apparently make e-selling more desirable to sellers. Increasing popularity of the Internet sales have caused thousands of companies such as IBM, Cisco and Nike to build their online sales channels besides distributing and selling products via offline sales channels (Cai et al. 2009).

### 1.1. Online versus Offline Channels

One characteristic of sales channels is the "structure". We refer to physical stores as "offline sales channel" and the Internet stores as "online sales channel". Examples of offline sales channel include retail stores such as Carrefour and Wal-Mart, manufacturer owned outlet stores such as Dell Outlet Store and HP Outlet Store, retail owned outlet stores such as Home Depot Retail Outlet Store, discount stores and resale stores such as Wal-Mart Discount Stores and The Computer Resale Store. The Internet bookseller "amazon.com" and the Internet retail store "ebay.com" are some examples of online sales channel. An online channel may offer advantages and disadvantages to both consumers and the sellers. Next, we outline these.

Some advantages of online channel for consumers are lower price, high availability levels, enhanced product options including customization, shopping comfortably without location and time restriction, no travel costs, and reduced search costs (Cairncross 1997, Brynjolfsson and Smith 2000, Ghose et al. 2006). Online channel has disadvantages for consumers as well. Not interacting with the product before buying, delay of gratification, high shipping cost, problems in returning or exchanging goods, and information security issues such as sharing credit-card information are some of these.

Consumers' channel preference between online and offline channel depends on some factors. Important factors include offline shopping transportation cost, distance to offline store, online shopping disutility cost, and the prices of the offline and online channel shopping. Product attributes may affect channel preference for consumers, too. The online channel may not be preferable for "experience goods" which are defined as the products that consumers prefer to experience before buying. The offline channel may not be preferable for "search goods" which are defined as the products that consumers require no experience before buying.

The advantages of online channel for sellers include increased profit margins, interaction with consumers, inexpensive data gathering, increased market coverage, providing better information on products, dynamic pricing, ease of customer segmentation and targeting, reduced inventory levels, and ease of cross selling products (Keck et al. 1998, Asdemir et al. 2002, Viswanathan 2005, Akcura and Srinivasan 2005, Guo and Liu 2008, Chiang 2010). The main disadvantage of online channel for sellers is the high cost of setting up a new channel. In addition, sellers need to coordinate the sales activities through multiple channels. When companies engage in e-commerce, they need to organize a delivery service besides product offering. To be competitive, this delivery service has to offer reasonable delivery times to consumer, which is costly to operate. In addition, there might be problems in returns. Since products cannot be tried or examined by consumers before receiving, returns in online channels are more frequent than returns in offline channels. For instance, online apparel retailers are reported to face a total return rate of 45% from customer orders (Tarn et al. 2003). The return operation is significantly more difficult for online sales than it is for offline sales as well. In addition to creating logistical difficulties, the high return volume also complicates the inventory planning process.

## 1.2. Direct versus Retail Channels

So far, we have discussed online versus offline channels. Another characteristic of channels is “ownership”. Manufacturers sell their products traditionally through intermediaries. We will use the term “retailer”, or the “retail channel” to refer to this intermediary. The retailer channel can be in online or offline structure. Retailer-owned traditional stores, discount stores, and resale stores are examples of retailer-offline channel; whereas, retailer-owned Internet stores are example of retailer-online channel. An alternative for manufacturers is to sell directly to consumers without any intermediary. This is referred to as the “direct channel”. The direct channel can also be in online or offline structure. Manufacturer-owned outlet stores and company stores are examples of direct-offline channel; whereas, manufacturer-owned Internet stores are examples of direct-online channel.

Figure 1.1 shows the sales channel matrix that illustrates the “ownership” and “structure” characteristics of the channels.

**Ownership**

| Structure | Direct | Retailer |
| --- | --- | --- |
| Offline | Company Stores and Outlets<br>(Sony Factory Outlet Store,<br>Apple Company Store,<br>Nike Outlet Store,<br>Hotiç Outlet Store) | Traditional Retail Stores<br>(Carrefour,<br>Home Depot,<br>Marks and Spencer,<br>Migros) |
| Online | Online Company Stores<br>(dell.com,<br>shopping.hp.com,<br>us.levi.com,<br>shop.vakko.com) | Online Retail Stores<br>(amazon.com,<br>ebay.com,<br>walmart.com,<br>hepsiburada.com ) |

Figure 1.1. Sales Channel Matrix

Establishing a direct channel offers certain advantages to a manufacturer. These include higher profit margins, direct contact to end consumers, controlling the service level, improving the company image, collecting sales data, improved demand forecasting and operations planning. On the other hand, the direct channel might be costly to set up. In addition, it requires the manufacturer to learn new skills in sales, marketing and distribution.

There are advantages and disadvantages of direct versus retail channel for consumers. Consumers make their choices between these two channels based on some factors. Consumers' search rates (i.e., the willingness to search the product in the other channel when there is a stock out in the desired channel) and consumers' sensitivity to price variations in different channels are some of these. Another important factor is whether the consumers are loyal to the brand or to the retail store. Store-loyal consumers value sales support and retailer advice, whereas, brand-loyal consumers value buying their favorite brand with the most advantageous price.

## 1.3. Dual Channel Strategy

A manufacturer need not use only the "retail channel" or only the "direct channel" to reach consumers. He may sell through both channels at the same time, which is known as a "dual channel" strategy[1]. The material and information flows in these three types of channel strategies are shown in Figure 1.2.

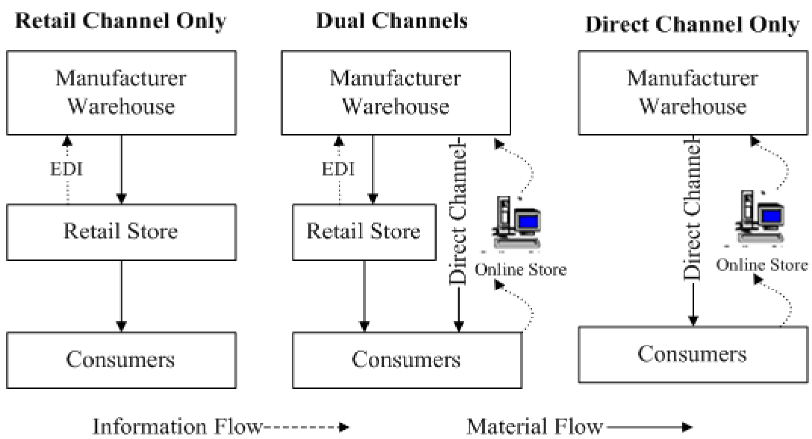



Figure 1.2. Types of Channel Strategies (Chiang and Monahan 2005)

[1] Some marketing researchers study the case of at least two different channels, which is known as "multi channel" distribution. We will simply focus on the two-channel version, the dual channel case.

We discussed that both the direct and the retail channels can be either in online (i.e., through the Internet) or offline (i.e., through physical stores) structure. In the rest of this thesis, we will focus on a manufacturer's dual channel strategy in which the direct channel is in online structure and the retail channel is in offline structure. Other combinations are also observed in practice, and these can be studied as extensions to our work.

Consumers derive certain benefits from a manufacturer's dual channel strategy. Increased options for shopping, improved customer service levels and reduced prices are some of these (Rhee and Park 2000, Hendershott and Zheng 2006, Agatz and Fleischmann 2008).

The advantages of using a dual channel for the manufacturer include serving to the customers from different segments, creating economies of scale and synergies, increased profit, negotiation power, recognition and brand loyalty, reduced double marginalization, better understanding of customer needs and shopping patterns, and improved channel efficiency (Chiang et al. 2003, Driver and Evans 2004, Boyacı 2005, Kumar and Ruan 2006, Agatz and Fleischmann 2008, Chiang 2010). In some cases, manufacturers may prefer to use dual channel strategy not for increasing the share of their own channels' profit, but for promoting the existing retail channel to increase its sales volume and profit. Chiang et al. (2003) report that even if manufacturers do not sell anything online and just open a direct channel to provide information on their products; they have an indirect profit growth of 7% due to increased sales in their retail channels.

Although many manufacturers select dual channel as their optimal sales channel strategy, few of them achieve success. When manufacturers establish direct channels, they become competitors to their retail channels. Manufacturers and retailers may compete in price and service (Boyacı 2005, Geng and Mallik 2007, Ryan et al. 2008, Chen et al. 2008, Chiang 2010). Retail channels might react to this, leading to "channel conflict" (Tsay and Agrawal 2004). In this case, both the retailers and the manufacturers might be worse off. Next, we study channel conflict in detail.

### 1.3.1. Channel Conflict

A research conducted by MIT (2001) states that channel conflict issues faced by manufacturers when introducing a direct-online channel can be grouped under three categories. These are threatening the relationship with the current channel, coordination problems between channels, and destroying the traditional consumer segmentation criteria. Next, we discuss these in detail.

First, retailers may threaten manufacturers with not selling their products. For example, the retailer Home Depot warned its thousands of suppliers by sending letters about not competing with the company via their online channels, otherwise the company would be hesitant to make business with its competitors (Brooker 1999). In particular, the retailers' reaction against the online channel might be aggressive when retailers' sales support to consumers is high. That is the reason why Levi Strauss and Liz Claiborne stopped investing in their direct online channels.

Second, coordination problems arise due to decentralized decision-making, communication difficulties, lack of information management and standardization, and language differences between channels. For instance, Citibank and Nomura Securities are reported to suffer from lack of integration and standardization between different sales channels (MIT 2001).

Third, when consumers are faced with multiple channels (one being retailer-offline and the other being direct-online), consumer segmentation and differentiation becomes difficult. The differences in prices or service levels between the channels may cause one channel to capture the sales of the other channel, which is known as "cannibalization". For example, consumers may take advantage of the retail-offline channel by receiving pre-sales service and advice from sales personnel, before buying from the direct-online channel. To understand these issues better, one first needs to determine the factors that affect consumers' channel choice. In their purchase decision, consumers choose the channel that provides them with the highest utility. In case of a stock out, they may choose to buy from the other channel(s), which is known as "channel switching". There are more specific reasons for why customers switch channels. Consumers' online purchase versus offline purchase intentions, price search intention, search and evaluation efforts, and products' search and experience attributes are the most important ones (Gupta et al. 2004). For example, Gupta et al. (2004) argue that consumers who prefer to purchase online have perceptions of less channel risk, search effort, and evaluation effort; but, more price search intention in comparison to the consumers who purchase offline.

Results of channel conflict can be grouped in two as retailer-related results and consumer-related results. Retailer-related problems may cause big losses for both manufacturers and retailers. Main retailer-related problems are retailers' unwillingness to share information with manufacturers, retailers not responding to online customers' complaints, and retailers' reduced sales efforts and future investments (MIT 2001, Kumar and Ruan 2006). For example, Kodak's marketing strategy as being a supplier for its retailers and a direct seller to its end customers lead to retailers being unwilling to share customer information and choices with the firm (MIT 2001). Consumer-related problems include consumer dissatisfaction and confusion, and changing consumer behavior. For example, J.Crew promoted the same products cheaper with special offerings in their online store in comparison to their retail stores. As a result, consumers who used both channels are confused and felt "cheated" (MIT 2001). In addition, consumers may show significantly different behaviors such as not having loyalty to both channel, and tending to buy from the cheapest channel or the one, which provides the most advantage.

### 1.3.2. Dual Channel Coordination

Many companies have to deal with dual channel problems. Companies such as Compaq, IBM, HP, Sun Microsystems, Ethan Allen Interiors Inc., Travelocity, Estee Lauder, Bobbi Brown Cosmetics, Mattel and Intuit manage to apply different strategies to make retailers involved in business while they are accompanied by the direct sales channels (Tsay and Agrawal 2004). The success of such firms lies on knowing how to avoid channel conflict. Some practical strategies for avoiding channel conflict are consistency in price and offerings, differentiating channels from each other, increased communication between channels, promoting channel partners, standardization of technologies and language through the whole supply chain, restricting the usage of the online channel (such as geographic restrictions), and redirecting online channel customers to retail channel for order fulfillment (Carlton and Chevalier 2001, Webb 2002 cited by Driver and Evans 2004, Tsay and Agrawal 2004, Cattani et al. 2006, Dumrongsiri et al. 2008, Mukhopadhyay et al. 2008, Zhang 2009, MIT 2001).

Retailers should be well informed about changing customer needs and business structures and they should be convinced that the direct-online channel would not totally replace the traditional-retail channel. One strategy may be to “segment” the consumers such that the consumers who prefer to buy online will be served through the direct-online channel; whereas, the consumers who prefer to shop from physical stores will be served through the retail-offline channel.

Channel switching may be prevented by increasing the switching costs. To this end, customized services can be provided for consumers, and the channel value can be increased by differentiating the services provided. Firms are free to select the combination of different features to affect the consumer choices, and to position themselves in the market. The manufacturers’ direct-online channels may differentiate the information bundle, user interfaces, product representation, customized services, purchase support and flexibility, and transportation services to set themselves apart from the offline channels. The retail-offline channels, on the other hand, may differentiate themselves through selection of store location, design and ambiance, transfer method, customer service, product variety and organization.

It is crucial to achieve “coordination” if a manufacturer is to benefit from the dual channel strategy. Coordination is aligning the incentives of individual supply chain members with the objectives of the whole supply chain. Three important coordination areas for a dual channel system are on pricing, procurement and distribution design (Cattani et al. 2004). Regarding the delivery options, for example, Men’s Warehouse uses its existing depots for meeting direct channel orders, while Home Depot allows consumers to pick up online orders from its stores, and J.C. Penney’s provides both options (Alptekinoglu and Tang 2005). Researchers investigate ways of coordinating the channels by using “supply chain contracts”. These contracts align the incentives of channel members, and help the chain achieve the efficiency of centralized decision-making. We discuss the related contract types and their effectiveness in coordinating dual channels in Section 2.2.

Retailers can be supported to use online solutions in order to add value to the distribution activities of online channel shopping. IBM recognizes that being successful in the long term with the direct channel strategy does not mean eliminating retailers and connecting with consumers only directly, but to encourage retailers to be included into the business with strong Internet technology (Keck et al. 1998). As a result, retailers will not be reacting to this new channel, and instead adapt themselves to the new business model. For example, NuSkin, a company of health support, provides an extranet for its retailers. By using this technology, the company lets retailers check new product information, track their sales volume, and receive online selling support (Keck et al. 1998).

Switching to a dual channel sales strategy also requires a change within the manufacturer's own organization and sales processes. If the managers cannot foresee these requirements, the result may be a failure. Employees can be resistant to the changes, since they think that online sales would not require any sales representatives. Actually, however, the new system requires sales people with their changed roles and work definitions. Strategically thinking managers will play an important role in getting people involved and be adapted into these changes.

### 1.3.3. Manufacturers' Optimal Channel Strategy

Manufacturers' optimal channel strategies depend highly on how consumers choose between the two channels. In the marketing literature, this is captured as the "segmentation" of the consumer population. Segmentation refers to how the consumer population will be divided between the two channels. In Section 1.1. and Section 1.2., we discussed how the structure (i.e., online or offline) and the ownership (i.e., direct or retailer) of the channels affect the consumers' channel choices. When customers are heterogeneously distributed in terms of their channel preferences, dual channel strategies may be successful in reaching all consumer types and increasing the market coverage.

Manufacturers need to consider some other factors besides consumers' channel preferences while deciding on their optimal channel strategies. These include product attributes (i.e., search vs. experience goods), marginal costs and profits, online order fulfillment, transaction and return costs, flexibilities of channels, competitors' strategic decisions, attractiveness of other brands in the same product category to the retailers, and information provision function of the online channel (King et al. 2004, Hendershott and Zheng 2006, Kumar and Ruan 2006, Zhang 2009).

Figure 1.3 presents the "Channel Conflict Strategy Matrix" developed by Accenture Consulting Group. This matrix allows one to determine the optimal change strategies for a manufacturer to minimize the channel conflict by analyzing the forces and opportunities for change. Market power is about whether the product (i.e., the manufacturer) or the retailer is more important for consumers. Channel value can be considered as the additional value that a specific retailer provides to the consumer over what the manufacturer provides. If the retailer provides extra value to consumers, his channel value is defined as “significant”.

| **Market Power** | Channel Value Added: Insignificant | Channel Value Added: Significant |
|---|---|---|
| Retailer controls consumers | *Forward Integrate*<br>• Identify new value proposition<br>• Act fast/independently<br>• Fill gaps in channel coverage | *Cooperate*<br>• Look for win-win, grow the pie<br>• Seek compromise<br>• Look to sell new products through new channels |
| Manufacturer controls consumers | *Compete*<br>• Create internet-enabled direct link to consumers<br>• Shift volume to new channel through promotions | *Lead*<br>• Define appropriate approaches for the channel<br>• Make initial investment |

Figure 1.3. Channel Conflict Strategy Matrix (Driver and Evans 2004)

When the market power of the retailer is high and its channel value is significant, this can result with the highest conflict between the manufacturer and the retailer. This is because the retailer positions himself equal to the manufacturer and demands cooperation. In such a situation, the manufacturer should cooperate with the retailer to maximize the total value created.

### 1.3.4. The Integration Level of Channels

In order to decide on the integration level of dual channel members, four business dimensions should be taken into consideration which are brand, management, operations and equity (Gulati and Garino 2000). These are related to creating a new brand name for the online channel or not, managing the channels together or separately, operating the channels in the same way or not, and owning the online business or outsourcing it.

The degree of vertical and horizontal integration determines the requirement for coordination and opportunities created. We discuss integration along two characteristics: structure (i.e., online vs. offline) and ownership (i.e., direct vs. retail).

For online versus offline channels, there are two alternatives. The first is operating a separate (dedicated) supply chain for the online channel. The second is to include the online channel into the existing supply chain by cooperating with partners in the offline channel (Seifert et al. 2006). In the second option, offline stores may be serving as local distribution centers of the online channel since the excess inventory in offline stores can be used to meet orders from the online channel.

For integration of channels, ownership plays important role. Below in Figure 1.4., four alternative supply chain models are presented. In model 1, an independent third company opens an online sales channel (e.g., Amazon.com). In model 2, the existing retailer opens an online channel to increase the options for consumers (e.g., Gap). In model 3, the manufacturer opens a direct-online channel to sell its products in addition to the existing retail channel (e.g., Nike). This alternative is what we study in this thesis. In model 4, full integration is achieved where the manufacturer owns both the online and the retail channels.

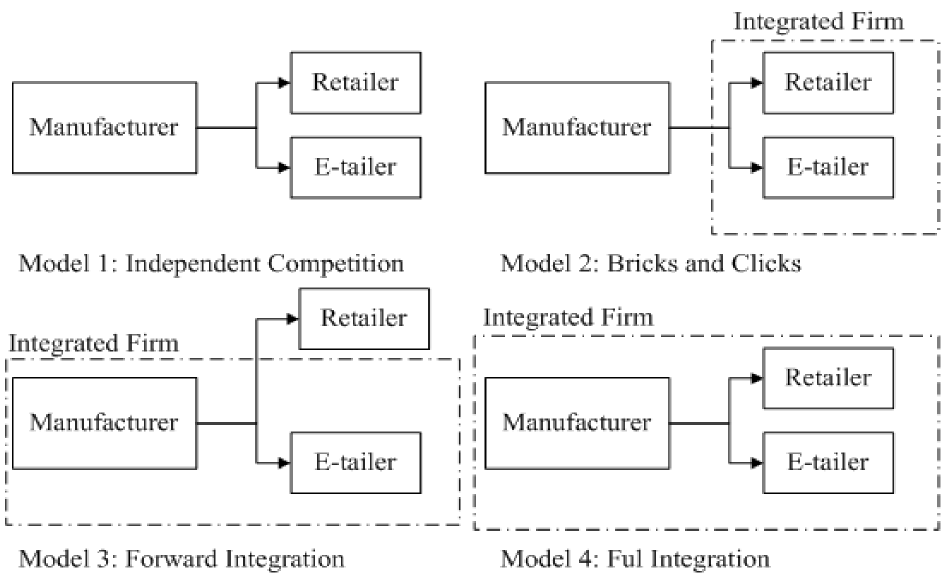



Figure 1.4. Integration in Dual Channel Models (Cattani et al. 2004)

Although the integration of direct and retail channels increases total system performance, reduces channel inventory levels and lost sales for the whole supply chain, whether to integrate the retail channel with the direct channel has been a discussion for a long time. Gulati and Garino (2000) provide the example of Barnes and Noble. This company established its own online channel barnesandnoble.com as a separate firm. Even though this online company enjoyed many advantages such as quickness on decision-making, having flexibility, creating own culture and quality, Barnes and Noble suffered a lot due to the decentralized structure of the online business from its offline stores. Despite the advantages of integration, some managers continue to believe that direct operations should be distinguished from the retail operations. Viswanathan (2005) argues that when channels are different in any core parameters, instead of being tightly integrated with the same pricing and segmentation strategies across channels, firms would benefit by segmenting the consumers according to their channel preferences, and developing appropriate pricing strategies for each segment. Thus, to integrate or not should not be the only question. Instead, deciding on the degree of integration and method of integration specific to a company are more important. Gulati and Garino (2000) provide examples on different integration policies as follows: Rite Aid bought a part of Drugstore.com's equity and made a partnership, KB Toys bought 80% stakes of BrainPlay.com and changed its name to KBkids.com while using the expertise of the company as a joint venture, Office Depot created its own website and highly integrated its physical and virtual operations.

So far, we discussed dual channel management, channel conflict, coordination and integration issues. By definition, these issues are related to the strategic interactions between multiple decision-makers. For instance, the dual channel problem involves the interaction between a manufacturer and a retailer where the profit of each firm depends on each other's decisions. Researchers model and study such interactions using "game theory" (see, for example, Fudenberg and Tirole 1991), which has been extensively used in the supply chain literature (Cachon 2003). Although commonly employed in literature, it is known that the assumptions of game theory and economic decision-making models are known not to hold when human beings make decisions in relevant real-world settings (Kahnemand and Tversky 1979). To this end, operations management researchers have started conducting "decision-making experiments" with human subjects to test the validity of theoretical models, and to understand the behavioral factors leading to deviations from theoretical predictions. Next, we discuss these.

## 1.4. Experiments

Experiments with human decision-makers have been used to check the validity of theoretical outcomes. Growth and development of game theory in 1940s led to the growth in experimental studies because game theory provides human behavior predictions that are suitable for experimental validation. Especially, game theoretic models that have assumptions of price rules, information availability and individual reactions are very suitable for experimental analysis (Bendoly et al. 2006). After the acceptance of experimental studies by the economics community, experimental research expanded to analyze the gaps between established economics theory and experimental results (Bendoly et al. 2006). However, since experiments are used in very limited research areas, their usage has not reached to its full potential yet. Recent findings of human behavior and perception have influenced economics, finance, accounting, law, marketing and strategy fields significantly; however, their influence on operations field so far has been very limited (Gino and Pisano 2008).

Even though behavioral studies take very limited place in the operations literature, they are expected to cover many areas of the operations management (OM) field in the future. Gino and Pisano (2008) propose five different research areas for the so called “behavioral operations” field. These are replication studies, theory-testing studies, theory-generating studies, adaptation studies and OM-specific studies. Replication studies are used to replicate or test the already existing behavioral theories with operations management data. Theory-testing studies are used to test operations management theories in a laboratory setting. Theory-generating studies are used to analyze existing operations management models with revised assumptions related to managers’ real decisions and biases. Adaptation studies are used to analyze operations management problems by focusing on behavioral reasons. Lastly, OM-specific studies are used to analyze important operations management problems by mixed methodologies of lab experiments, field-based research, modeling, and empirical analysis.

### 1.4.1. Methodology of Experiments

The experimental methodology steps can be broadly defined as follows.

#### 1) Defining the Purpose of the Experiment

In the first step, the purpose of the experiment should be clearly defined. Purpose of the experiment might include answering some questions about observable phenomena, to improve a mathematical model, to verify a prediction of the theory or to solve a problem.

#### 2) Setting the Hypothesis

Next, the "hypotheses" of the experiment are formed. "Hypothesis" is a proposed explanation of a phenomenon, which can be tested to be proved. In statistical hypothesis testing, two hypotheses are compared. These are the "null hypothesis" and the "alternative hypothesis". The null hypothesis is the hypothesis that rejects the relation between phenomena whose relation is to be investigated. The alternative hypothesis is the hypothesis that accepts the relation between phenomena whose relation is to be investigated.

#### 3) Experimental Design

Experimental design includes the decisions on the instructions, the physical environment, the software (if any) and other decision parameters. The instructions must cover all information necessary for subjects (participants) to perform the experimental task. Instructions can be printed on a paper and distributed to subjects at the beginning of the experiment (game). They should be clear and well defined (not too long and not too short) to lead subjects to play in a desired way.

At this step, the physical environment of the experiment is determined. Laboratories are usually selected as experiment facilities. Behavioral experiments do not require any specific machines and instruments; thus, a pencil and a paper might be sufficient in many cases. Recently, experiments are run mostly on computer networks.

This brings the advantages of quick information processing, quick interaction of subjects, standardization, reduced mistakes, and ease of data storage (Guala 2005).

Deciding on the software for the experiment is another design issue. There are some standard software packages to be used in behavioral experiments; however, these might not perfectly fit to a specific experiment and usually requires some modification. To overcome this issue, special-purpose software can be developed for the experiment.

In addition, other decision parameters such as the number of subjects or subject groups, subjects' information levels, input parameters, the number of game replications and financial incentives should be specified at this step.

Subjects are usually selected from university students. However, in some experimental games managers and business people are used as subjects to avoid bias due to using inappropriate subject groups. In contrast to this, according to a study of Bolton et al. (2008), when the games played with different subject groups (i.e., students, managers and employees) are compared, no significant difference is observed in the game results. In addition, students are observed to perform better than managers in learning the game and optimizing their decisions based on their experience in the game (Bolton et al. 2008).

Economists believe that financial incentives are crucial for ensuring subjects to behave in the same manner as in the real world when they participate in the experiment. Hence, financial incentives are usually used to motivate subjects. Subjects' financial incentive levels can be defined between some ranges and a limit value can be specified for the overall financial incentive amount. However, there is a trade-off between the number of subjects and financial incentive level of each subject. Hence, the number of subjects should be determined optimally.

### 4) Conducting the Experiment

This step includes pilot and original runs of the game. Before conducting the experiment, it should be tested on a small number of subjects, using a small number of replications. These runs will show if the experiment works smoothly and if data is generated properly. If there are problems related to processes and data generation, these can be eliminated before running the original experiment.

Before running the original experiment, subjects are trained on the game, where the rules and steps of the game are clearly explained. Next, subjects' understanding of the game is tested with some pilot (warm-up) runs. Subjects need to be “matched” to each other in experiments that require interaction (such as experiments that deal with social factors). How this matching is done is an important experimental decision. For example, subjects can be matched randomly at each replication or they can play the whole game with the same partner; they can be matched against computers; they may or may not know their partner. Finally, the original experiment is conducted and data is created at each replication.

**5) Data Analysis and Hypothesis Testing**

After data generation is completed, one moves to the analysis step. In this step, first, experimental data is cleaned by discarding questionable data and outliers. Next, one begins the statistical analysis of data. A characteristic or measure obtained from a sample is named a “statistic”. Statistics is divided into two types, which are “descriptive” and “inferential”. Descriptive statistics cover methods for summarizing data. Data can be summarized via “numerical descriptors” and “graphical tools”. Numerical descriptors include mean and standard deviation; whereas, graphical tools include various kinds of charts and graphs such as the scatter plot, histogram, bar chart, and box plot. Descriptive statistics are frequently used to summarize experimental output data in this step (Keser and Paleologo 2004, Corbett and Fransoo 2007, Loch and Wu 2008, Pavlov and Katok 2009).

Inferential statistics let researchers make statements about some unknown aspect of a population from a sample. Inferential statistics are used to test hypothesis, to estimate parameters, to forecast future behavior, to describe association (correlation), and to model relationships (regression). Inferential statistics is divided into two types, which are “parametric” and “non-parametric”. Parametric inferential statistics models and tests assume that distributions of the assessed variables are in the families of the known parametric probability distributions. Some test examples include one-sample t-test, two-sample t-test, and Pearson’s correlation test. In the non-parametric inferential statistics models, the model structure is not defined from the beginning; however, it is determined from the data. Non-parametric statistical tests make no prior assumptions on the distributions of the assessed variables. Some test examples include Kolmogorov-Smirnov test, chi-square goodness of fit test, Wilcoxon Mann-Whitney test, Spearman’s correlation test. As we stated before, hypotheses are set in the first step of an experiment. In the analysis step, these hypotheses are statistically tested using experiment data via parametric and non-parametric statistical tests.

Statistical tests are mainly classified in three categories with respect to their functionality. These are testing of differences between independent groups, testing of differences between dependent groups, and testing of relationships between variables. Table 1.1 (Statsoft 2010) presents the related parametric tests and their non-parametric counterparts used in each category.

Table 1.1. Statistical Test Categories and Tests in Each Category

| **Category** | **When to Use** | **Parametric Test** | **Non-parametric Test** |
|---|---|---|---|
| Differences between independent groups | Comparing two samples regarding the mean value of the variable analyzed | T-test | the Wald-Wolfowitz runs test, the Mann-Whitney U test, the Kolmogorov-Smirnov two-sample test |
| | Comparing multiple samples regarding the mean value of a the variable analyzed | ANOVA (analysis of variance)/ MANOVA (multiple analysis of variance) | Kruskal-Wallis analysis of ranks, the Median test |
| Differences between dependent groups | Comparing two variables measured in the same sample | T-test for dependent samples | Sign test, Wilcoxon's matched pairs test, McNemar's Chi-square |
| | Comparing multiple variables measured in the same sample | repeated measures ANOVA | Friedman's two-way analysis of variance, Cochran Q test |
| Relationships between variables | Defining relationship between two variables | standard correlation coefficient test | Spearman R, coefficient Gamma, chi-square test, the Phi coefficient, the Fisher exact test |
| | Defining relationship between multiple variables | | Kendall coefficient of concordance |

### 1.4.2. Experimental Models

In literature, experimental models are classified in different ways:

- Environment (Bendoly et al. 2006):
    - Industrial experiments where subjects are real workers performing their own job.
    - Laboratory experiments where subjects are performing a controlled version of job.
    - Situational experiments where subjects are informed about situations and asked about their actions for each.
- Research Process (Amaldoss et al. 2008):
    - Deviating from model's equilibrium predictions and later converging to them: This can be used for observing the change in the results when each parameter is not set according to the equilibrium values. That shows the sensitivity of model to the each parameter.
    - Subjects' not preserving their equilibrium position in repeated games: This is used to develop new models and predict strategic decisions better.
    - Testing the models' validity with similar real world situations: This is used to better understand the specific points and their effects on the model predictions.
- Target (adapted from Amaldoss et al. 2008):
    - Analysis of learning effect: Subjects' choices may not show the equilibrium predictions at the beginning stages; however, they may agree on the equilibrium predictions at later stages. This changing behavior of subjects can be explained by the learning effect.
        - Population models: Population models investigate the populations' behavior change due to experience.
        - Individual models: Individual models investigate the individuals' behavior change due to their own experience.
            - Experienced learning models: The model focuses on the learning relation between subjects' current decisions related to their previous decisions and experiences.

            - Direct learning models: The model focuses on the learning relation between the latest strategy of the subject and the optimum strategy achieved through all previous stages.
    - Theory improvement: These are developed by relaxing the some of the limiting assumptions of Nash equilibrium.
        - Quantal response equilibrium models: Assumption of “subjects are making decisions without errors” is relaxed.
        - Cognitive hierarchy models: Assumption of “subjects’ beliefs are mutually consistent” is relaxed.
    - New mechanisms and strategic choices: Changing existing designs of mechanisms and strategic choices by experiments leads to a change in subjects’ behavior and increases total profit.

### 1.4.3. Contributions of Experiments to Academic Research

Experiments help researchers test and refine theories, and construct new ones (Amaldoss et al. 2008, Croson and Gächter 2010). For example, experiments can be used to check the comparative statics of a theory or to determine the applicable domains of a theory. They enable the development of new models to better predict strategic decisions. Experiments can show which observed anomalies are related with a specific field context, and which can be generalized and related to other fields.

In addition, experiments can be used to measure individual’s preferences across genders, interesting social groups, cultures and demographical properties. Recently, experiments are used to investigate social considerations and individual decision biases, specifically the loss aversion and reflection effects (Schultz et al. 2007, Ho and Zhang 2008, Loch and Wu 2008, Bendoly et al. 2010, Katok and Wu 2009). Experiments allow to demonstrate behavioral biases regarding the empirical outcomes and to determine the strategies to prevent these biases (Croson and Donohue 2002).

Experiments offer certain advantages over field studies. In experiments, many parameters such as interaction rules, reward systems and information flows can be controlled which may not be possible in field studies (Bolton and Kwasnica 2002). Experiments simplify the world by involving a little context, artificial settings and abstract instructions. They also enable testing of certain policies before implementation in the field. For example, Hewlett Packard is reported to use experiments in testing some of its marketing policies before implementing them with its retailers (Chen et al. 2008).

### 1.4.4. Reasons for Experimental Deviations from Theory Predictions

There is usually a disconnection between theoretical models' prediction and real-life observations. The main reasons for this disconnection are lack of awareness of decision-makers, lack of applicability of tools, and lack of information. However, the common factor in this difference is human behavior. For example, Katok and Wu (2009) show that the contracts, which are analytically proved to coordinate a supply chain, such as the buyback and revenue sharing contract, may not experimentally result in coordination due to certain behavioral factors affecting the subjects' decision-making. In real life, such behavioral factors as lack of trust between supply chain partners, incentive misalignment and risk aversion prohibit operational success (Bendoly et al. 2006). Table 1.2 presents classification of behavioral issues related to operating systems and processes. In this perspective, acquisition of information, processing of information, interpretation of outcome and receiving feedback are four activities to be distinguished.

Table 1.2. Classification of Behavioral Issues Related to Operating Systems and Processes (Gino and Pisano 2008)

| Activity Area | Behavioral Issue |
|---|---|
| Acquisition of information | information avoidance, confirmation bias, availability heuristic, salient information, illusory correlation and procrastination |
| Processing of information | anchoring and insufficient adjustment, representativeness heuristic, law of small numbers, sunk cost fallacy, planning fallacy, inconsistency, conservatism, and overconfidence |
| Interpretation of outcome | wishful thinking and illusion of control |
| Receiving feedback | fundamental attribution error, hindsight bias, and misperception of feedback |

Table 1.3 provides examples of behavioral issues that cause experimental deviations from theory predictions, as stated in literature.

Table 1.3. Behavioral Issues Causing the Actual Decisions to Deviate from Theory Predictions

| **Behavioral Issue** | **Explanation** | **Stated By** |
|---|---|---|
| perception of gain and loss factors | such as risk perception (averse, seeking, neutral), risk reflection (being risk-averse in gains but risk-seeking in losses) and framing | Amaldoss et al. 2008, Bendoly et al. 2010 |
| controlling bargaining power | tendency of exerting influence over other channel member | Pavlov and Katok 2009 |
| social preferences related to instinctive concerns | about the other chain member's welfare, existence of a positive relationship between channel members and instinctive wishes of having more profit than the other channel member | Loch and Wu 2008 |
| inappropriate goals | tendency of exerting influence over other channel member | Croson and Donohue 2002, Su 2008, Bendoly et al. 2010, Katok and Wu 2009 |
| no perfect rationality | having limited ability to solve complex problems | Croson and Donohue 2002, Su 2008, Bendoly et al. 2010, Katok and Wu 2009 |
| unexpected feedback loops or unexpected dynamics | getting/providing unnecessary feedbacks | Bendoly et al. 2010 |
| automated response (1), and lack of cognitive effort (2) | responding automatically (1), and not performing cognitive effort while decision-making (2) | Croson and Gächter 2010 |
| regency | forgetting past events | Bostian et al. 2008 |
| reinforcement | focusing more on the payoff achieved from the actual decisions less on the counterfactual payoffs that could be achieved from other decisions | Bostian et al. 2008 |
| overconfidence | tendency of overestimating the accuracy of estimates | Bendoly et al. 2010, Croson et al. 2008, Gino and Pisano 2008 |
| law of small numbers | considering small samples as representative of the populations from which they are drawn | Bolton and Katok 2008, Gino and Pisano 2008 |

In addition to above stated behavioral issues, researchers found more specific behavioral biases in OM-specific contexts. For example, a bias that is observed in the "beer game" (refer to Section 2.3. for more information) when analyzing the "bullwhip effect" is "underweighting the supply line" in ordering decisions (Barlas and Özevin 2004, Croson and Donohue 2005). This bias refers to the participant's tendency to order more than necessary in a given period due to underestimating the goods in the supply line (i.e., goods ordered, but not received yet). Another such bias observed in the beer game is the "pull to center effect" which refers to the average order quantities to being too low when they should be high and too high when they should be low (Bostian et al. 2008). This effect is caused by (1) ex-post inventory error bias: aiming to decrease ex-post inventory error, and (2) anchoring and insufficient adjustment bias: anchoring around a price-quantity combination from previous decisions or average demand, and making insufficient adjustments on it (Schweitzer and Cachon 2000, Keser and Paleologo 2004, Barlas and Özevin 2004, Bolton et al. 2008, Bolton and Katok 2008). Some examples of biases observed in different areas of operations management are stated below in Table 1.4 (Gino and Pisano 2008).

Table 1.4. Examples of Biases Observed in Different Areas of Operations Management

| **Behavioral Bias** | **Explanation** | **Operations Management Area** |
|---|---|---|
| anchoring and insufficient adjustment bias | taking a reference point and making adjustments around it | product development, project management, inventory management, forecasting, supply chain negotiation, resource allocation |
| overconfidence bias | tendency of overestimating the accuracy of estimates | inventory management, project management and development, service operations, employee learning |
| confirmation bias | individuals' tendency of searching information selectively | product development, supply chain management, forecasting |

These findings lead researchers to change their assumptions and include human behavior in their models to better predict the results and optimum strategies. Some proposed strategies to overcome human bias factors in decision-making are as follows. Bolton et al. (2008) provide demand distribution and expected profit information to the decision-makers during a behavioral experiment to make them order the optimal quantity. Katok and Wu (2009) express the importance of using decision support tools to increase total system profitability and to decrease waste by eliminating human bias factors in decision-making. In a newsvendor setting, Bolton and Katok (2008) define some institutional factors that may lead decision-makers to order the optimal stocking quantity as: (1) Using technology tools such as ERP to avoid unnecessary responses to short-term information; (2) Increasing employee experience via training programs; and (3) Limiting the possible order quantities.

Employee motivation and performance improvement is another area in which the identification of human decision biases is important. Bendoly et al. (2010) propose three strategies to overcome human decision biases related to motivational and performance factors: (1) Setting difficult, specific and measurable goals, which connect the outcome directly with the employees' performance; (2) Tracking and analyzing the differences between employees' goals and performance; (3) Providing interdependence of employees.

## 1.5. Our Study

The developments in the Internet technology and in third-party logistics have encouraged manufacturers to establish a “direct-online channel” and sell directly to end-consumers. Most manufacturers are now reaching their customers via “dual” sales channels composed of an owned direct channel and an independent retail channel. While the dual channel strategy has its advantages for the manufacturer, such as reaching different consumer types, it also introduces coordination issues between the manufacturer and the retailer. This is because the dual channel setting makes the manufacturer both a supplier and a competitor to the retailer. Researchers have been investigating these issues for some time, focusing mostly on price competition between the channels.

In this thesis, we study a manufacturer's dual channel strategy in a setting where the direct channel is in online structure and the retail channel is in offline structure. The channels compete in “service” to consumers, and the service levels in the two channels are characterized dependent on their channel structure. The online direct channel's service level is the delivery lead time to consumers, whereas the offline retail channel's service level is the product availability. The channels cater to a heterogeneous customer market, where customers choose between channels according to a detailed consumer channel choice process that takes the service levels of the channels into account.

Developing a dual channel strategy for the manufacturer requires a specification of the "contract type" between the manufacturer and the retailer. Under a "wholesale price contract", the manufacturer sells the products to the retailer with a unit wholesale price $w$ and the retailer cannot return unsold products to the manufacturer. Under a "buyback contract", the retailer can return unsold products to the manufacturer for a unit buyback price $b$. In general, introducing a buyback price along with a given wholesale price reduces the retailer's cost of overage, and hence, provides incentive for the retailer to order more. Literature has shown how a buyback contract can coordinate a simple manufacturer-retailer supply chain. However, it is not clear how much advantage the buyback contract will provide in a dual channel environment because of the nature of the relation between the firms.

Our work is based on two theoretical studies. Chen et al. (2008) developed the three-stage game-theoretical dual channel model that we use. In stage I, the manufacturer sets the contract parameters. In stage II, the two firms simultaneously determine their operational decisions that define the service levels in the two channels: The retailer determines his product availability level and the manufacturer determines the delivery lead time in the direct channel. In stage III, stochastic consumer demand is realized and consumers prefer from which channel to buy.

Gökduman and Kaya (2009) extended the wholesale price contract model of Chen et al. (2008) to a buyback contract model. Gökduman and Kaya (2009) compare the performances of the two contracts and show, for example, that the buyback contract model (BCM) can outperform the wholesale price contract model (WPM) in terms of total supply chain profits.

In order to understand if these models provide reasonable predictions when human decision-makers are involved, one can use behavioral experiments with human subjects in the roles of the manufacturer and the retailer. The main reason of conducting behavioral experiments is to capture the effects of behavioral factors, which are not covered by the theoretical models. For instance, the theoretical models assume that the decision-makers have perfect knowledge of the best response functions, and make their operational decisions with respect to the Nash equilibrium concept. However, it is known that the assumptions of game theory and economic decision-making models do not hold when human beings make decisions in relevant real-world settings (Kahnemand and Tversky 1979). It would be important to know the effects of such “behavioral deviations” from theoretical predictions if we want theory to offer value to practice.

By conducting two preliminary behavioral experiments that focus only on some part of the model, Chen et al. (2008) showed that the wholesale price contract model can be used to predict the characteristics of the observed results and the changes in the results. However, they also detected significant dispersion in the observed data and deviation of the results from the theoretical predictions.

This thesis contributes to this stream of research by presenting a detailed experimental study of the two aforementioned dual channel models (WPCM and BCM). The wholesale price contract experiments were conducted previously in HP Laboratories, USA. We prepared and conducted the buyback contract experiments in Sabancı University, Turkey. We coded the buyback version of the experimental code, using special-purpose software called MUMS. We conducted 6 experimental sessions at the CAFE (Center for Applied Finance Education) computer lab of Sabancı University. Human subjects are selected from Sabancı University Fall 2010/2011 MS 454 students who have the basic knowledge on supply chain management and contracts.

Our main research questions include (1) How successful are the theoretical models (wholesale price contract and buyback contract models) in predicting the outcome of the game between the manufacturer and the retailer? Related to this question, (2) Is the Nash equilibrium a good predictor of the outcome of the operational decisions game at stage II? (3) Can the manufacturer anticipate the outcome of the operational decisions game and set contract parameters accordingly at stage I? (4) Are the subjects learning to make better decisions over time? (5) How is the experimental performance of the buyback contract model relative to the wholesale price contract model? (6) What factors might be affecting a participant’s ordering decision?

The remainder of the thesis is organized as follows. In Chapter 2, we summarize the related literature. In Chapter 3, we describe the game-theoretic dual channel model under the wholesale price contract (WPCM) and buyback contract (BCM), and summarize the theoretical results. In Chapter 4, we analyze the wholesale price contract experiments (WPCE). In Chapter 5, we analyze the buyback contract experiments

(BCE). In Chapter 6, we compare the experimental results related to the two contracts. In Chapter 7, we analyze the factors that affect the behavior of subjects. In Chapter 8, we discuss our main results, conclude and mention future research directions.

# CHAPTER 2

## CHAPTER 2 : LITERATURE REVIEW

In this chapter, we review the related literature in three parts. First, the literature on supply chain coordination will be reviewed. In this part, available coordination mechanisms will be discussed. Second, the literature on dual channel supply chains will be examined. In this part, competition and coordination issues between the manufacturer-owned direct channel and independent retailer channel are discussed. Third, the literature on behavioral experiments on operations management and supply chain management will be reviewed.

### 2.1. Supply Chain Coordination

We begin our supply chain coordination discussion by introducing the "newsvendor problem", which is a fundamental inventory management problem under uncertain demand. The newsvendor problem considers a short life-cycle product with a single selling season, facing random demand. The random demand $D$ for the product has a cumulative distribution function $F(.)$ and density function $f(.)$. The decision-maker needs to determine how many products to buy (his order quantity $Q$) prior to the selling season. He pays a wholesale price $w$ per unit he buys and gains $p$ per sale to his consumers. He does not have a chance of a second order during the season, and unsold products are salvaged at a unit price of $v$.

Not having the product when a consumer demands costs the decision-maker $c_u = p - w$. This cost is called the cost of underage. Having an unsold product at the end of the selling season costs the decision-maker $c_o = w - v$. This cost is called the cost of overage. The optimal number of products to order depends on the costs of underage and overage, and on the distribution of the random demand.

The cost of underage is equal to the marginal benefit of having one more unit of inventory in stock when demanded. The cost of overage is equal to the marginal cost of having one more unit of inventory in stock when not demanded. The random demand $D$ will be less than or equal to $Q$ with a probability of $F(Q)$ and more than $Q$ with a probability of $1 - F(Q)$. Thus, the expected marginal benefit of stocking one more unit is $c_u(1 - F(Q))$ and the expected marginal cost of stocking one more unit is $c_o F(Q)$. The optimal order quantity needs to strike a balance between the marginal benefit and the marginal cost of having an extra unit. That is, we have $c_u(1 - F(Q)) = c_o F(Q)$). Hence, the decision-maker's optimum order quantity $Q$ should satisfy:

$$F(Q) = \frac{c_u}{c_u + c_o},$$

where $c_u/(c_u + c_o) = (p - w)/(p - v)$ is referred to as the "critical fractile". Let $Q^r$ represent the optimal order quantity that satisfies the above condition. This quantity is found by

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

where $F^{-1}$ is the inverse cumulative distribution function of demand $D$. See Kaya and Özer (2008) for more details on the newsvendor problem.

The standard newsvendor problem explained above is concerned with only one decision-maker that can be referred to as the "retailer" because he purchases products to satisfy random consumer demand. A more complicated picture arises if one also considers the "manufacturer" who supplies the retailer with products. Assume that the manufacturer produces to order, that is, he produces after receiving the retailer's order. Let the unit production cost at the manufacturer be "$c$". The retailer and the manufacturer together are referred to as the "supply chain".

One can show that the retailer's optimal order quantity $Q^r$ given above is not the optimal one for the supply chain as a whole. That is, while maximizing the retailer's expected profit, this order quantity does not maximize the supply chain's expected profit. The quantity that maximizes the supply chain's expected profit would be

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

The retailer does not optimally order this quantity, because his costs of underage and overage are different from the supply chain's. This problem, known as the "double marginalization' problem in literature, leads to channel (or, supply chain) inefficiency. Sprengler (1950) first introduced double marginalization concept to literature. Double marginalization can be defined as the distortion of a supply chain member's relative cost structure due to the introduction of a transfer price into a channel (Donohue 2000). In the problem we discussed, the wholesale price between the manufacturer and the retailer causes double marginalization. If the wholesale price was equal to the unit production cost, double marginalization would be eliminated. However, this solution is not implementable, as it leaves zero profit to the manufacturer.

In literature, supply chain coordinating contracts are designed to extract the full supply chain system efficiency by aligning the economic incentives of the involved firms (Cachon 2003). This provides decreased inventory cost, reduced flow times, and a better match between supply and demand (Croson and Donohue 2002). Some of the main contract types mentioned in literature that achieve coordination are buyback (Pasternack 1985, Donohue 1996, Emmons and Gilbert 1998, Cachon and Lariviere 2005), revenue sharing (Cachon and Lariviere 2005), quantity flexibility (Pasternack 1985, Tsay 1999), sales rebate (Taylor 2002), quantity discount (Jeuland and Shugan 1983, Weng 1995, Chen et al. 2001), and two-part tariff (Tirole 1988) contracts.

Coordination can also be viewed as finding a way to properly share demand risks. Cachon and Lariviere (2005) propose buyback and revenue sharing contracts, which work in such a mechanism. These two contracts are efficient on risk sharing by dividing the supply chain revenue in desired portions to the two parties for any realization of demand. In a buyback contract, the manufacturer buys back unsold products from the retailer by paying more than the salvage value. Thus, the manufacturer shares the retailer's excess stock risk. This contract is studied first by Pasternack (1985) under the name "providing partial credit for all returns". Donohue (2000) study the buyback contract in an environment where the manufacturer runs two modes of production with different wholesale prices, and the retailer has an option of updating his demand forecast. Emmons et al. (1998) study the use of buyback contract in a setting where the retailer's demand is price-dependent. In the revenue sharing contract, the manufacturer reduces the wholesale price to make the retailer order more products, and as a return obtains a portion of the retailer's sales revenue.

Quantity flexibility contract is another mechanism to coordinate channels (Tsay 1999). According to this contract, first, the manufacturer and the retailer agree on an initial order quantity. The retailer commits to buy at least some percentage of this initial order quantity while the manufacturer commits to deliver up to some percentage above this quantity. Using this contract, the cost of market demand uncertainty can be divided between the manufacturer and the retailer, so that the supply chain optimal outcome can be achieved (Tsay 1999). In a related study, Pasternack (1985) shows that proving full credit for a partial return of goods achieves channel coordination, but the retailer demand distribution determines the optimal return percentage. Hence, the strategy is not useful in a multi-retailer environment, because retailers have different demand distributions.

In a sales rebate contract, the manufacturer pays the retailer for products sold to consumers. Taylor (2002) discusses two types of channel rebate contracts: In a linear channel rebate, the manufacturer pays the rebate to the retailer for each sold unit. In a target channel rebate, the rebate is paid for each unit sold above a target level. Taylor (2002) shows that the target-rebate contract can coordinate the channel.

In a quantity discount contract, the unit wholesale price that is paid by the retailer to the manufacturer is a decreasing function of the retailer's order quantity. Jeuland and Shugan (1983) show that quantity discounts can coordinate the supply chain. Weng (1995) studies the quantity discount contract in a basic form. Chen et al. (2001) extend his work by considering multiple retailers and general cost structures.

The two-part contract (also known as a two-part tariff) has two terms: A wholesale price and a lump-sum side payment from the retailer to the manufacturer. We refer the readers to Tirole (1988) for more details about this contract.

The literature discusses many other contract types that can coordinate a manufacturer-retailer supply chain such as the penalty contract, consignment contract, and options contract. For a comprehensive review of the literature, we direct the readers to Cachon (2003), and Kaya and Özer (2008).

## 2.2. Dual Channel Distribution Systems

Here we review the literature on dual channel distribution systems composed of a manufacturer-owned direct channel and an independent retailer channel. In this setting, the manufacturer is both a supplier and a competitor of the retailer. As a result, there exists both vertical and horizontal competition. Vertical competition exists between the manufacturer and the retailer while horizontal competition exists between the direct channel and the retail channel.

Channel competition and coordination issues in a dual channel setting with a manufacturer (upstream member) being a competitor and supplier of a retailer (downstream member) have recently been studied by many researchers. Within the dual channel management literature, a number of researchers investigate the causes of and the ways to avoid channel conflict. These researchers include Keck et al. (1998), Allen et al. (2000), Carlton and Chevalier (2001), Driver and Evans (2004), and Tsay and Agrawal (2004). Below we discuss some important findings of this literature.

A number of researchers study the competition of a manufacturer and a retailer in a dual channel setting. Kumar and Ruan (2006) analyze competing manufacturers and retailers in the same product category. They investigate the reasons of variation in the optimal channel preference of manufacturers according to product, firm and market characteristics. They found that the manufacturer's decision of introducing an online channel depends on the retailer's strategy in the absence of the online channel. The manufacturer's decision of the wholesale price changes the retailer's sales effort, which depends on the relative attractiveness of the manufacturer's product to the retailer in comparison to other manufacturers' products. Dumrongsiri et al. (2008) investigate the variation in optimal channel preference of manufacturers related to product characteristics and consumer preferences. Ryan et al. (2008) study a dual channel setting of direct-online and retail channels under price competition for the first time, and assess the effects of price competition to the profits of each member.

Boyacı (2005) and Chiang (2010) study vertical and horizontal inventory competition between dual channel members when there is stock-out-based substitution. Geng and Mallik (2007) study inventory competition and allocation strategies with undercut options in a dual channel setting. Chen et al. (2008) is the first paper in availability-based service competition integrated with a consumer channel choice model in dual channel settings. Similar to Boyacı (2005), Chiang and Monahan (2005), Dumrongsiri et al. (2008) and Chiang (2010), Chen et al. (2008) assume that the total demand is stochastic. Viswanathan (2005) study the effects of different channel flexibilities (i.e., firms being independent of each other), network externalities and switching costs on competition between online, offline and dual channel firms.

Bernstein et al. (2009) analyze the effects of free riding and rival products on a direct channel. Mukhopadhyay et al. (2008) investigate the effect of dual channel distribution strategy on the retailer's cost for a value-adding retailer under information asymmetry.

Some researchers consider retailer-oriented models. Alptekinoglu and Tang (2005) study the retailer's direct-online channel strategy in terms of distribution methodology. Guo and Liu (2008) analyze a retailer's optimal store opening decision, where the manufacturer's direct channel entry is a potential threat for the retailer's business. Competing retailers are studied by King et al. (2004), Hendershott and Zheng (2006) and Zhang (2009). Zhang (2009) study the retailer's dual channel and price advertisement strategies. The author finds that advertising offline prices in the online channel coordinates the channels. King et al. (2004) study pricing policy and channel strategies in an infinitely repeated two-stage strategic gaming model with multiple retailers. In each period of the game, first, the retailers decide on their sales channel strategies, and later consumers make their channel preferences. Hendershott and Zheng (2006) analyze an environment of a direct-selling manufacturer with multiple retailers that compete in price. They assume that consumers' channel values are heterogeneously distributed. The authors find that the manufacturer's opening a direct channel combined with competition and price discrimination between retailers result in lowered retail prices. As a result, consumers' welfare, manufacturer's profit and overall welfare of the system are increased.

Coordination of multiple distribution systems is also discussed in the literature. A Forrester report states that retailers understand their mission of serving customers together with manufacturers to overcome channel conflict (Allen et al. 2000). Coordination issues may depend on the product properties or system structure. For instance, Ryan et al. (2008) demonstrate that dual channel systems of highly price-sensitive products, which do not seem to replace each other, are more crucial cases to be coordinated. In other words, the requirement to increase system performance by coordination increases when consumers are more sensitive to direct channel price. However, when consumers' sensitivity to competitor price increases, the total system profit increases due to the substitution of two channels, and hence, there is less need for coordination. Some dual channel coordination mechanisms studied in literature are optimal pricing policies (Tsay and Agrawal 2004, Cattani et al. 2006, Kurata et al. 2007, Cai et al. 2009), revenue sharing (Ryan et al. 2008, Ganfu et al. 2009, Chiang 2010, Geng and Mallik 2007), improving retail services (Yan and Pei 2009), value added channels (Mukhopadhyay et al. 2008), profit sharing (Yan 2008), vendor managed inventory (Bernstein et al. 2006), penalty contract and two-part compensation commission contract (Boyacı 2005). Next, we discuss these mechanisms in more detail.

The increasing trend to use dual sales channels leads manufacturers and retailers to cooperate on some profit sharing strategies to improve channel coordination and total supply chain performance. There are many examples of coordinating dual channel distribution systems using adequate pricing schemes. Cai et al. (2009) study price discount contracts and pricing schemes to achieve coordination, and show how a consistent pricing scheme may avoid channel conflict by providing more profit to the retailer or to the manufacturer. According to the study, price discount contracts result better than non-contract scenarios with manufacturer-Stackelberg, retailer-Stackelberg and the Nash game theoretic models. Kurata et al. (2007) study mixture of markup and markdown prices to coordinate the supply chain. Tsay and Agrawal (2004) show that revising the wholesale price can increase the total performance of the dual channel system when the reduction in wholesale price affects the retailer's sales performance. Since the sales effort measurement is not easy to handle, using some other strategies such as "referral to direct" and "referral to retailer" are suggested. These strategies consist of using a dual channel strategy, but directing customers from one channel to another for the purchase. Cattani et al. (2006) suggest a specific equal pricing strategy for manufacturer's direct channel and retail channel prices, which provides most profit for manufacturers and advantages for retailers and customers. However, this strategy can achieve its targets only when direct channel is less convenient than retail channel.

Revenue sharing is another common strategy to coordinate dual channel systems. Cachon and Lariviere (2005) show that a revenue sharing contract can coordinate a supply chain with one manufacturer and one or many retailers. Since the strategy requires sharing revenue and cost information, it may be difficult to implement in practice. Chiang (2010) also propose a contract called "inventory and direct revenue sharing" where supply chain members agree to share the inventory holding cost of the total supply chain. The manufacturer also agrees to share some portion of the direct sales revenue with the retailer. However, this contract poses difficulties in tracking inventory and point of sale data. When demands are price dependent, coordination might be more difficult, since both price and inventory decisions should be coordinated in each channel. Ryan et al. (2008) study two different coordination contracts between a manufacturer and a retailer that compete on demand-determining price. These are the minimum price constrained revenue sharing and gain/loss sharing contracts. The author suggests using dual channels with price and product discrimination for coordination. Ganfu et al. (2009) illustrate the coordination mechanism of a direct channel revenue sharing contract under free riding and price competition. Geng and Mallik (2007) propose a reverse revenue sharing contract, which achieves coordination with a fixed franchise fee and penalty.

Adding value to a channel, and differentiating or improving services can help in coordinating dual channel systems. Yan and Pei (2009) investigate the strategic role of the retailer in a dual channel environment where channel members strategically cooperate to increase total system profit and coordination. They show that improved retail services manage to coordinate the dual channel supply chain, improve each supply chain member's performance, and protect retailers from being eliminated from the market due to increased competition between channels. Mukhopadhyay et al. (2008) propose a value-adding system in which a manufacturer sells the basic form of a product through its online channel and allows the retailer to add value to the product to differentiate it from its basic version. Such a system would be highly applicable to hi-tech industries such as computer or electronics industries. Although there is an increase in total system profit with the value adding system, the total profit is not equal to the one achieved in the integrated system case.

Video rental and franchising industries (fast foods, hotels and motels etc.) have been using profit sharing to coordinate channels for a long time. Yan (2008) analyzes the strategic role of members under profit sharing in a dual channel supply chain. He uses a Nash bargaining model and measures the effect of Bertrand and Stackelberg models to total supply chain profit. Comparing the profits of each supply chain member in the retailer-only system with the profits in a dual channel system, he observes that both the retailer and the manufacturer benefit, and obtain more profit in comparison to the non-profit sharing system.

Other coordination mechanisms of dual channel systems are as follows. Bernstein et al. (2006) propose a vendor managed inventory model (VMI) to coordinate the two-echelon supply chains with one manufacturer and multiple retailers. Boyacı (2005) propose a penalty contract, which consists of a wholesale price and a unit penalty price paid by retailer to manufacturer for each unmet consumer demand. However, this contract is hard to implement due to the requirements of tracking and auditing the lost sales in retail channel. Thus, Boyacı (2005) propose an alternative coordination mechanism called a two-part compensation commission contract. In this contract, the retailer continues to determine how much to order from the manufacturer, whereas the manufacturer obtains all sales revenue of the retailer. In return, the manufacturer pays the retailer a sales commission for each extra sales unit above a threshold value. The manufacturer compensates the retailer for each unit of inventory when retailer sales are below the target. Boyacı (2005) shows that the optimal supply chain profits can be obtained by choosing the target levels as required.

## 2.3. Behavioral Experiments

The effects of human behavior in operations management field has recently been a popular subject among researchers. Bendoly et al. (2006) review operations management literature between years 1985 and 2005 in terms of behavioral issues, and categorize the existing papers in three behavioral sections, which are intentions, actions and reactions. Majority of operations management papers discussing behavioral issues are on inventory management and production management. Product development, quality management, procurement and strategic sourcing, and supply chain management are other popular areas. Gino and Pisano (2008) study the theoretical and practical results of behavioral and cognitive factor effects on operations management, which is build on the earlier work of Bendoly et al. (2006). A deep understanding of human behavior and cognition in production, efficiency and flexibility are mentioned as future research studies.

The Operations Management (OM) literature has produced a significant number of theoretical models regarding supply chain management. However, the validity of these models is generally not tested with experimental studies. Hence, there is a gap in literature on testing supply chain decision-making models. In fact, experiments are very suitable for analyzing the behavior in supply chains. This is mainly due to experiments' capability of measuring the scope of behavioral factors causing empirical regularities, understanding the relative strength of multiple causes for any supply chain issue, testing economics theory and operations theory, and measuring the effect of operational factors under the existence of behavioral factors (Croson and Donohue 2002). Existing experimental studies in supply chain management mainly focus on the newsvendor problem, coordination contracts, and the bullwhip effect.

Schweitzer and Cachon (2000) make the first laboratory study on the newsvendor problem by analyzing high and low safety stock conditions. They find that the order decisions deviate from optimal order quantities, and that receiving feedback and having experience do not have a significant impact on reaching the optimal order quantities. The authors have two explanations for these. First, subjects make their decisions as if they aim to decrease their ex-post inventory error (the absolute difference between current inventory decision and realized demand). Second, subjects have a bias of anchoring and insufficient adjustment. Contrary to Schweitzer and Cachon (2000), Bolton and Katok (2008) find that experience and feedback have significant contribution on the inventory decisions to reach the optimal by eliminating anchoring and insufficient adjustment bias. They show that the stock levels can be influenced to reach the optimal by institutional organization of experience and feedback. Bostian et al. (2008) analyze the "pull to center effect" in a newsvendor model by a laboratory experiment, and build an adaptive learning model for explaining individual decisions. They assess learning behavior by changing the frequency of information feedback and order decisions. Subjects in low decision frequency treatments have not improved their decisions round by round in comparison to the subjects in high decision frequency treatments.

Bolton et al. (2008) study the role of managerial experience in the newsvendor problem for the first time. They find that manager subjects use only historical demand data as their work experience to optimize decision-making, and they are not successful in using analytical information. However, student subjects utilize analytical information and task training better than manager subjects utilize, and improve their decisions towards the optimal inventory decision. Barlas and Özevin (2004) analyze effects of some experimental factors on the performance of subjects and the correctness of decision rules in stock management models. They cannot find an inventory model that completely explains the subjects' behavior. Corbett and Fransoo (2007) empirically analyze the decision-makers' risk profile effect on the newsvendor model. Finally, Croson et al. (2008) propose a behavioral model of overconfident newsvendors, which fits well to the observed suboptimal order behavior of decision-makers. The authors also design an incentive contract by price and salvage value adjustments that will lead the overconfident newsvendors make optimal orders.

A number of researchers conduct experimental studies in supply chain contracting. Katok and Wu (2009) study the behavioral aspects of the wholesale price, buyback and revenue sharing contracts between a manufacturer and a retailer. Their study is the first laboratory investigation on the performance of these contracts. Keser and Paleologo (2004) investigate a simple manufacturer-retailer relationship under a wholesale price contract experimentally. They find that the wholesale prices and order quantities are lower than predicted, but the efficiency of the supply chain is as predicted by the theoretical models. Ho and Zhang (2008) investigate two-part tariff and quantity discount contracts experimentally, and show that these contracts fail to coordinate supply chains due to the loss aversion effect. However, Su (2008) show that for a newsvendor model, a two-part tariff contract can be used to coordinate the supply chain when the decision-maker is bounded rational. When the decision-maker is unbounded rational, the supply chain can be coordinated by aligning individual incentives with social objectives via contractual transfers. Deviation of retailer orders from theory predictions is a very common problem. For solving this problem, Becker-Peth et al. (2009) provide a response function for modeling the relationship between the supply contract parameters and orders to optimize supply contracts. They assume that retailers are irrational but predictable. They replace the newsvendor model with a new one, which predicts orders placed more accurately. Using this model, the buyback contract is revised to better coordinate the supply chain.

Croson and Donohue (2002 and 2003), and Steckel et al. (2004) are among the researchers that study the "bullwhip effect" which is one of the reasons for coordination problems in supply chains. The bullwhip effect is first detected by Procter and Gamble in 1990s. The rate of birth in the United States was stable and the usage of diapers was in a steady rate; however, Procter and Gamble observed the oscillations of orders from distributors to its factories and from Procter and Gamble to its suppliers. Interestingly, variation of orders and inventory levels was increasing from downstream to upstream in the supply chain. The bullwhip effect denotes the increased oscillation of orders at each level and amplification of these oscillations as one goes to the upstream in the supply chain. This phenomenon is illustrated in Figure 2.1. The bullwhip effect is mostly caused by lack of communication between supply chain members, and it may result with overage and shortage of inventory, fluctuations in the batching of orders and shipments, reduced profit margins, and increased promotions and discounts which change the shopping behavior of consumers (Sheffi 2007).

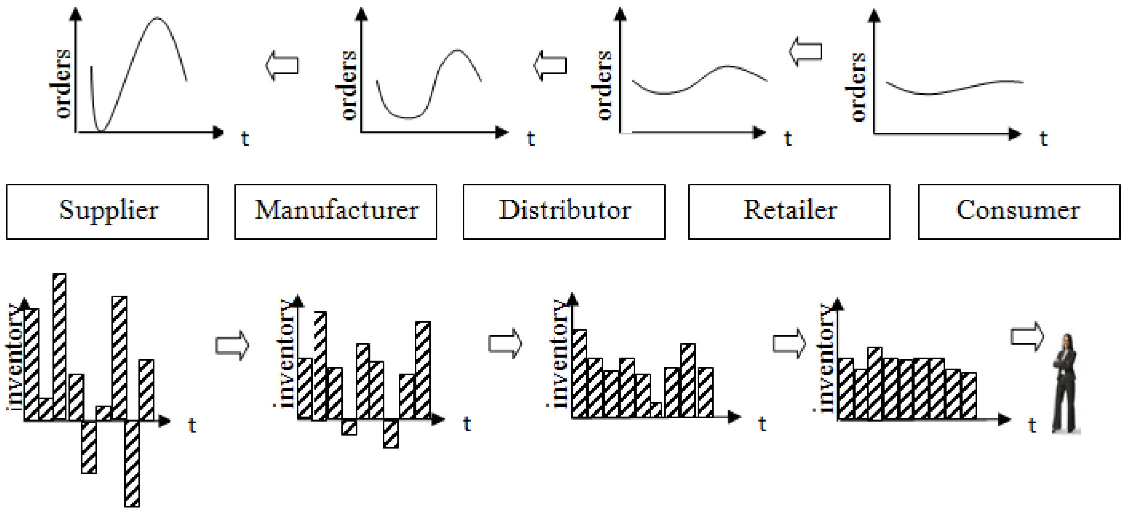



Figure 2.1. The Bullwhip Effect

Researchers study the bullwhip effect with a role-playing simulation developed at MIT in the 1960s called "the beer game". This game simulates a four-stage simple, linear supply chain, where players make ordering decisions based on their current inventory levels and customer orders. Four members of the supply chain in beer game are the manufacturer, the distributor, the wholesaler and the retailer. All members aim to maximize profit by avoiding out-of-stock situations and minimizing the excess stocks. The ordering and shipping delays between the stages make it difficult to match supply and demand for the decision-makers. Croson and Donohue (2002) study the behavioral aspects regarding the learning effect and communication in the beer game, which affect the inventory decisions. Croson and Donohue (2003) analyze the impact of point of sale (POS) data sharing between channel members in a beer game. They make a simulation experiment where the demand distribution is unknown. They observe that sharing POS data has some impact on reducing the bullwhip effect, specifically the order oscillations of upstream members. Steckel et al. (2004) study the effect of changes in order and delivery cycles, availability of POS information, and customer demand pattern on supply chain efficiency via a simulation experiment similar to the study of Croson and Donohue (2003). Short cycle time is found to be effective; however, sharing POS information is effective when demand is found to be S-shaped.

Most supply chain coordinating contracts focus on self interested and rational channel members while not taking into account social issues such as reciprocity, status seeking and group identity (Loch and Wu 2008). However, recent studies show that supply chain members consider social issues besides economic concerns while making decisions. Thus, social preferences may play a role in motivating individual subjects. As a result, social issues such as fairness, status seeking, other party's welfare and reciprocity have been entered into the supply chain management literature by researchers in developing contracting mechanisms. Some applications are as follows. Pavlov and Katok (2009) consider fairness and bounded rationality issues in the subjects' preferences while designing a supply chain coordination mechanism for a manufacturer-retailer system. When the manufacturer has full information on fully rational retailer's preference for fairness, the manufacturer can coordinate the channel by offering the retailer the minimum conditions required for the retailer to accept. Otherwise, when the retailer's preference for fairness is its private information and the retailer is bounded rational, the manufacturer cannot coordinate the supply chain. Loch and Wu (2008) study the effect of social preferences on economic decision-making in supply chain transactions. Subjects are assumed to have good relationship, and in a status-seeking condition at the beginning. Systematical deviation of subjects from the profit maximizing decision is found to be related to the conditional changes where a positive relationship promotes mutually profitable decisions of both parties, while, status seeking increases the competitive behavior of both subjects, and reduces the system efficiency and performance of subjects.

As we mentioned before, statistical tests are used to test hypotheses in behavioral experiments. Below in Table 2.1, some inferential statistical tests used by researchers to test hypotheses in experimental studies are summarized.

Table 2.1. Statistical Tests Used by Researchers to Test Experimental Studies

| Statistical Hypothesis Test | Used by |
|---|---|
| **1- Parametric tests** | |
| t test | Schweitzer and Cachon 2000, Barlas and Özevin 2004, Schultz et al. 2007, Bolton and Katok 2008, Katok and Wu 2009 |
| Multivariate Analysis of Variance (MANOVA) | |
| Wilks' lambda test | Loch and Wu 2008 |
| Hotelling's two group t-square test | Loch and Wu 2008 |
| **2- Non-parametric Tests** | |
| **a- One-sample tests** | |
| Non-parametric sign test | Croson and Donohue 2003 |
| One-sample Wilcoxon test | Katok and Wu 2009, Bolton et al. 2008 |
| Wilcoxon signed ranks test or Wilcoxon matched pairs test | Keser and Paleologo 2004, Kremer et al. 2007, Pavlov and Katok 2009, Becker-Peth et al. 2009 |
| Chi-square goodness of fit test | Bolton and Katok 2008 |
| Likelihood ratio Test | Su 2008 |
| **b- Two-sample tests** | |
| Two-sample Wilcoxon test | Kremer et al. 2007 |
| Mann-Whitney U test or Wilcoxon rank-sum test | Croson and Donohue 2003, Bostian et al. 2008, Bolton and Katok 2008, Loch and Wu 2008, Pavlov and Katok 2009, Katok and Wu 2009 |
| Spearman test | Bostian et al. 2008 |
| Multiple median test | Schweitzer and Cachon 2000 |

In addition to hypothesis testing, researchers also employ other statistical methodologies. For example, regression analysis is used to predict one variable (the dependent variable) by defining its relation with two or more other (independent) variables using an equation (Croson and Donohue 2003, Corbett and Fransoo 2007, Loch and Wu 2008, Bolton et al. 2008, Pavlov and Katok 2009, Becker-Peth et al. 2009). Correlation analysis is another methodology used to evaluate the association between two data sets (Keser and Paleologo 2004, Corbett and Fransoo 2007).

# CHAPTER 3

## CHAPTER 3 : THE MODEL AND THEORETICAL RESULTS

In this chapter, we first explain our theoretical models (i.e., wholesale price and buyback contract models), and then provide our theoretical results achieved by solving the models in Mathematica for different parameter settings.

### 3.1. The Dual Channel Model

Our behavioral experiments are based on the analytical models of Chen et al. (2008), and Gökduman and Kaya (2009). We provide these analytical models in this chapter. These researchers construct a dual sales channel model that considers a manufacturer who sells a product through his direct online channel and an independent retail channel. Both the manufacturer and the retailer are risk neutral. The sales price $p$ is determined exogenously, and it is the same in both channels. Hence, there is no price competition between the channels.

The models are based on availability-based service competition between the manufacturer and the retailer. The manufacturer's service level is determined by delivery lead time $t$ in his direct channel and the retailer's service level is determined by service level $\alpha$ in his retail store. Additionally, consumer channel choice is modeled and total demand is assumed to be stochastic. Chen et al. (2008) formulated the model under a wholesale price contract, whereas, Gökduman and Kaya (2009) extended the model to a buyback contract setting.

In both models, there are three stages. Stage I is called "contracting" where the manufacturer sets the contract parameters (wholesale price $w$ in the wholesale contract case, wholesale price $w$ and buyback price $b$ in the buyback contract case) and offers the contract to the retailer. The retailer accepts the contract if the contract provides at least his reservation profit level in expectation. The type of the contract that the manufacturer offers at stage I is the only difference between two models.

Stage II is called "operational decisions" where the manufacturer and the retailer decide on their own service levels in a simultaneous-move game. The retailer determines the service level $\alpha$, the probability of no stock-out in the sales season. The retailer orders the required number of products (his order quantity) $q$ to satisfy this service level from the manufacturer. The manufacturer does not have a capacity constraint and can satisfy the retailer's order prior to the selling season. The manufacturer determines the delivery lead time $t$, the time a consumer needs to wait between ordering from the online channel and receiving the product. The manufacturer incurs a cost of $m/t^2$ for setting up the direct channel, where $m$ is the direct channel cost parameter.

Stage III is called "consumers' channel choice" where consumers make buying decisions (to buy or not) and decide on which channel to buy from. Total demand (total number of consumers in the market) is denoted by $X$ which is a uniformly distributed random variable between 0 and $a$. Consumers make their decisions based on a consumer channel choice model that we explain in Section 3.2. According to this model, consumers consider the delivery lead time $t$ in the direct channel, the service level $\alpha$ in the retail channel, the product's sales price $p$, the product's value to consumers $v$, and the retailer inconvenience cost $k$ in their channel choice decision. The inconvenience cost denotes the cost of time and effort spent while visiting the retail channel for consumers. Hence, the total demand is realized according to a uniform distribution exogenously, and this total demand is shared between the channels based on the retailer's and manufacturer's decisions endogenously. Below in Figure 3.1, sequence of events is illustrated under the wholesale price contract. For ease of reference, we summarize the relevant notation in Appendix A.

Chen et al. (2008) solved the wholesale price contract model using backwards induction. First, they defined the expected demand in the direct and the retail channels based on the consumer channel choice model at stage III. Second, they showed the Nash equilibrium of the operational decisions game by characterizing the manufacturer's and the retailer's best response functions at stage II. Third, they found the manufacturer's optimal wholesale price contract ($w$) by using a grid search at stage I. Gökduman and

Kaya (2009) used the same method to determine the manufacturer's optimal buyback contract $(w, b)$ at stage I.

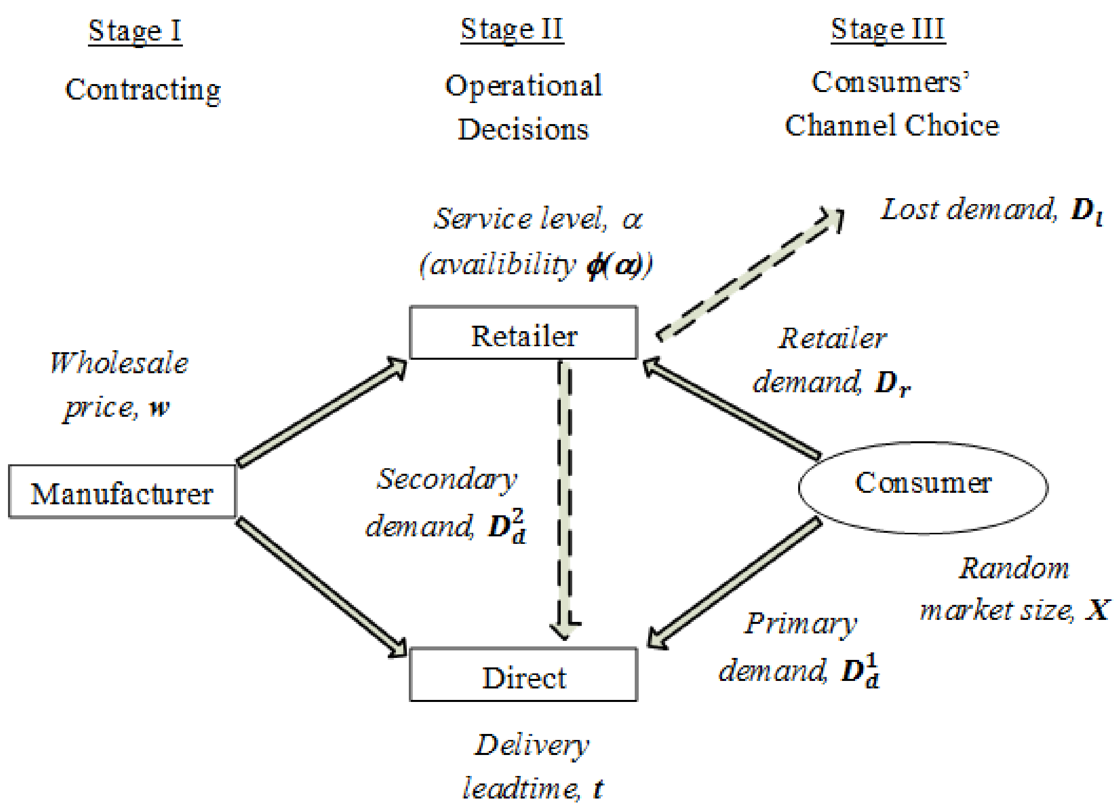



Figure 3.1. The Sequence of Events under the Wholesale Price Contract

### 3.2. Stage III: Consumers' Channel Choice

The consumer channel choice model is based on differentiating the consumers with respect to their willingness to wait before receiving the product. Consumers are assumed to be heterogeneous, uniformly distributed between 0 and 1, and indexed with the time-sensitivity index $d$. A low time-sensitivity index $d$ indicates that the consumer is a patient one, who can wait longer for the delivery of the product. The consumers who have low time-sensitivity index are more likely to prefer the direct channel.

A consumer with time-sensitivity index $d$ derives utility $u_d$ when buying from the direct channel. This utility is affected from the product's sales price $p$, product's value $v$ (where $p < v$) and the manufacturer's delivery lead time decision $t$ as follows:

$$u_d(d) = v - p - dt.$$

In this function, $dt$ states the reduction in the utility of the consumer with index $d$ due to waiting $t$ time units to receive the product.

Because the product might not be always available in the retail channel (depending on the retailer's service level α), the utility of a consumer from the retail channel is an expected value. This expected utility is affected from product's sales price $p$, product's value $v$, retailer's service level α, and retailer's inconvenience cost $k$ as follows

$$E[u_r] = \phi(\alpha)(v - p) - k.$$

The term $\phi(\alpha)$ is the retailer's product availability level, which denotes the probability of a consumer finding the product in the retail store. To assure a positive utility for consumers (i.e., $E[u_r] \geq 0$), the retailer's service level should satisfy the minimum service level constraint

$$\alpha_{min} \equiv \left\{ \alpha \in [0,1] \middle| \phi(\alpha) = \frac{k}{v-p} \right\}. \tag{1}$$

Each consumer makes his channel decision by comparing his utility from the two channels. Considering all consumers' choices, four streams of demand are generated in the model as illustrated in Figure 3.1: Retailer's demand $D_r$, primary demand in the direct channel $D_d^1$, secondary demand in the direct channel $D_d^2$, and lost demand $D_l$. Direct channel demand is always satisfied within the delivery lead time, whereas retailer demand is only satisfied when the retailer has on-hand inventory. Thus, only the retail channel incurs the lost demand.

The decision process of the consumer with index $d$ is as follows:

- When $u_d \geq 0$, the consumer considers the direct channel as an alternative and two cases are possible:
  - When $u_d \geq E[u_r]$; the consumer buys directly from the direct channel. These consumers constitute the primary demand $D_d^1$ in the direct channel.
  - When $u_d < E[u_r]$; the consumer visits the retailer first and buys the product if it is available. These consumers constitute part of the retailer demand $D_r$. If the product is not available at the retail store, the consumer buys from the

direct channel. These consumers constitute the secondary demand $D_d^2$ in the direct channel.

- When $u_d < 0$, the consumer does not consider the direct channel, and two cases are possible:
  - When $u_d < E[u_r]$ and $E[u_r] \geq 0$; the consumer visits the retailer first and buys the product if available. These consumers constitute rest of the retailer demand $D_r$. If the product is not available at the retail store, the consumer does not buy from the direct channel either. These consumers constitute part of the lost demand $D_l$.
  - When both $u_d < 0$ and $E[u_r] < 0$; the consumer does not prefer to buy from either channel. These consumers constitute the rest of the lost demand $D_l$.

The heterogeneity of consumers (represented with their index $d$) and their decision process leads to the segmentation of the consumer population. To determine this segmentation, we define two boundary index values:

- $d_1$ denotes the index of the consumer who is indifferent between buying from the direct and the retail channel.
- $d_2$ denotes the index of the consumer who is indifferent between buying from the direct channel and not buying at all.

These values are expressed as:

$$
\begin{aligned}
d_1 &\equiv \min\left\{\{d \mid u_d(d) = E[u_r]\},\ 1\right\} \\
&= \min\left\{\left[(v-p)\left(1-\phi(\alpha)\right) + k\right]/t,\ 1\right\}, \\
d_2 &\equiv \min\left\{\{d \mid u_d(d) = 0\},\ 1\right\} \\
&= \min\{(v-p)/t,\ 1\}.
\end{aligned} \tag{2}
$$

In the most general case, $\mathrm{d}_1$ and $\mathrm{d}_2$ divide the consumer population into three segments. This is shown in Figure 3.2.

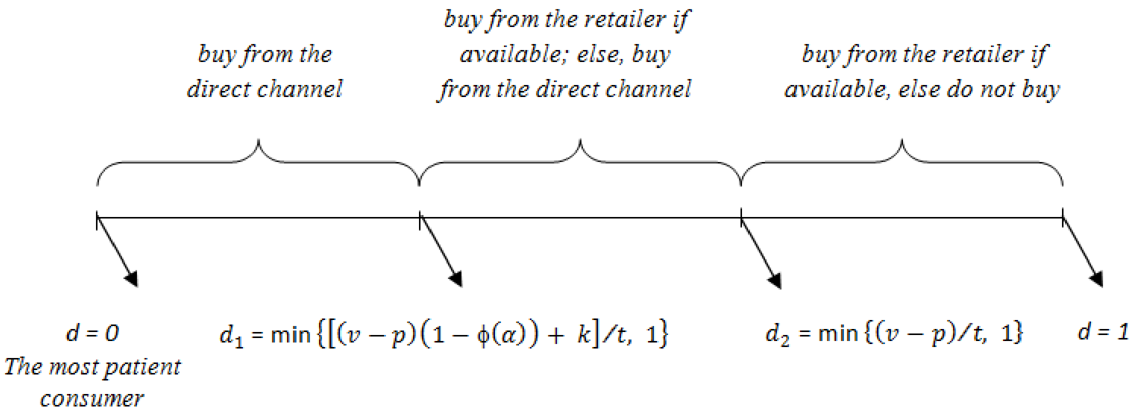



Figure 3.2. Consumer Segmentation

Consumers with a time-sensitivity index lower than $d_1$ buy directly from the direct channel because $u_d(d) \geq E[u_r]$. These consumers constitute the first segment.

Consumers with a time-sensitivity index higher than $d_1$ and lower than $d_2$ first visit the retailer. If the product is available, they buy the product there; otherwise, they buy the product from the direct channel. This is because $0 \leq u_d(d) \leq E[u_r]$. These consumers constitute the second segment.

Consumers with a time-sensitivity index higher than $d_2$ only visit the retail channel. If the product is available, they buy it; otherwise, they do not consider buying the product from the direct channel. This is because $u_d(d) < 0$ and $E[u_r] \geq 0$. These consumers constitute the third segment.

Note that the utility from the retail channel does not depend on the time-sensitivity index $d$ of the consumers. If the retail channel provides the minimum service level, it becomes operative and all consumers derive positive utility from the retail channel. The issue with the retail channel is that it cannot guarantee product availability.

The following lemma summarizes the demand in each channel depending on the manufacturer's delivery lead time decision $t$.

For a given service level α, there are four possible outcomes as shown in Lemma 1. When the manufacturer sets a delivery lead time $t$ smaller than the threshold value $t^e \equiv (v-p)(1-\phi(\alpha)) + k$, all consumers buy from the direct channel and the retailer becomes inoperative. In this case, there is only one market segment, since $d_1$ =1 and the manufacturer eliminates the retailer.

***Lemma 1.*** *Random demand in the direct and retail channel are as follows:*

| *Delivery lead time range* | $t \leq t^{e\dagger}$ | $t \in (t^e, v-p]$ | $t \in (v-p, \infty)$ | $t \to \infty$ |
|---|---|---|---|---|
| *Retailer's status* | *Inoperative* | *Operative* | *Operative* | *Operative* |
| *Direct channel coverage* | *Full* | *Full* | *Partial* | *None* |
| *Retailer demand* ($D_r$) | *0* | $(1-d_1)\,X$ | $(1-d_1)\,X$ | $X$ |
| *Primary demand* ($D_d^1$) | $X$ | $d_1X$ | $d_1X$ | $n/a^{\dagger}$ |
| *Secondary demand* ($D_d^2$) | $n/a$ | $[D_r-q]^+$ | $\frac{d_2-d_1}{1-d_1}[D_r-q]^+$ | $n/a$ |
| *Lost demand* ($D_l$) | $n/a$ | *0* | $\frac{1-d_2}{1-d_1}[D_r-q]^+$ | $[D_r-q]^+$ |

† $t^e \equiv (v-p)(1-\phi(\alpha)) + k$ *and n/a: not applicable.*

When the manufacturer sets a delivery lead time between $t^e$ and $v-p$, the manufacturer separates the market in two segments. By setting $d_2$ to 1, the manufacturer ensures that all consumers derive positive utility from buying the product through both channels. Thus, there is no lost customer in this case. As the consumer's time-sensitivity index is a uniformly distributed random variable, the primary demand of direct channel is equal to $D_d^1 = d_1X$. The retailer demand is equal to the rest of the total market demand which is $D_r = (1-d_1)\,X$. When the retailer has sufficient inventory to meet this demand, (i.e., when, $D_r \leq q$), the retailer satisfies all demand in his channel. Otherwise, the retailer cannot satisfy $[D_r-q]^+$ units of his demand and these consumers constitute the secondary demand in the direct channel.

The manufacturer may set a delivery lead time greater than $v-p$. By setting such a delivery lead time, the manufacturer segments the market into three, since $d_2 < 1$. In this case, the manufacturer serves part of the consumers through his direct channel, allows the retailer to satisfy some part of the demand through the retail channel and lets some consumers leave the system without buying the product from either channel. Primary demand of the direct channel and retailer demand are the same as in the previous case. In addition, there is lost demand. Among unsatisfied retailer consumers, $(d_2-d_1)/(1-d_1)$ percent have $u_d(d) \geq 0$ and these constitute the secondary demand $D_d^2$ in the direct channel. The rest have $u_d(d) < 0$ and they constitute the lost demand $D_l$.

Lastly, if the manufacturer sets a very long delivery lead time (i.e., $t \rightarrow \infty$), the direct channel operation is (almost) shut down and the retail channel becomes the only alternative. In this case, there is only one market segment again, since $d_1 = d_2 = 0$.

Retailer's availability level also affects the market segmentation. If $\phi(\alpha) = k/(v-p)$ and $t > v - p$, there are only two market segments because $d_1 = d_2 < 1$. In this case, no consumer visits the direct channel when they cannot find the product in the retail channel.

### 3.3. Stage II: Operational Decisions

Here we study the retailer's and the manufacturer's problems at stage II. As the wholesale price contract is a special case of the buyback contract with $b = 0$, we analyze the operational decisions under a buyback contract in a general form. We emphasize the changes in the solution under a wholesale price contract when necessary.

In this section, first the objective functions of the retailer and the manufacturer are defined. Then, the best response functions of the retailer and the manufacturer are characterized. Finally, the algorithm to find the Nash equilibrium of the operational decisions game is explained.

#### 3.3.1. Retailer's Problem

Here, the retailer's best response service level $\alpha^*(t)$ to the manufacturer's delivery lead time $t$ decision is characterized. We first present the following Lemma that provides the retailer's order quantity, availability level, and expected sales for a given service level.

***Lemma 2.*** *For a given service level $\alpha$,*

*(i) The retailer optimally orders $q(\alpha) = a\alpha\big(1 - d_1(\alpha)\big)$ units of product;*

*(ii) The corresponding availability level is $\phi(\alpha) = \alpha\big(1 - ln(\alpha)\big)$;*

*(iii) The expected sales in the retailer is $E[min\{D_r, q\}] = a\big(1 - d_1(\alpha)\big)(\alpha - \alpha^2/2) = q(1 - \alpha/2)$.*

Note that part (ii) shows the relationship between the retailer's service level $\alpha$ and the corresponding availability level $\phi(\alpha)$.

Recall that retailer's optimal order quantity $q$ is a function of his service level decision $\alpha$, which affects the demand $D_r$ at the retail channel through the consumers' channel choice process. If demand at the retail channel is higher than the retailer's stocking level, the retailer ends up with lost sales (i.e., no backordering is possible), whereas if demand is less than the stocking level, the retailer ends up with excess inventory. This excess inventory can be sold back to the manufacturer under a buyback contract but this has a zero salvage value under a wholesale price contract.

For a given buyback contract $(w, b)$, the retailer's expected profit as a function of the service-level $\alpha$ is given by:

$$\prod_r (\alpha) = pE[\min\{D_r, q\}] - wq + b(q - E[\min\{D_r, q\}]). \tag{3}$$

In this equation, $E[\min\{D_r, q\}]$ denotes the expected sales of the retailer and $(q - E[\min\{D_r, q\}])$ denotes the expected excess inventory of the retailer at the end of the selling season. With a buyback contract, the retailer's expected profit is increased by $b(q - E[\min\{D_r, q\}])$ relative to the expected profit with a wholesale price contract, because the manufacturer buys the unsold units from the retailer at the end of the selling season.

Substituting $q$, $\phi(\alpha)$ and $E[\min\{D_r, q\}]$ from Lemma 2 to the Equation 3, we have

$$\prod_r(\alpha) = a\alpha\big(1 - d_1(\alpha)\big)\left(p - w - (p - b)\frac{\alpha}{2}\right). \tag{4}$$

Substituting $d_1$ from Equation (2), the retailer's problem becomes

$$\max_\alpha \prod_r(\alpha) = \frac{a\alpha}{t}\Big(t - k - (v - p)\big(1 - \alpha(1 - \ln(\alpha))\big)\Big)\left(p - w - (p - b)\frac{\alpha}{2}\right), \tag{5}$$

subject to $\alpha \in \{\alpha_o, [\alpha_{min}, 1]\}$,

where $\alpha_{min}$ is defined in Equation (1) and $\alpha_o$ is defined such that $d_1(\alpha_o) = 1$. The term $\alpha_o$ is introduced to prohibit an undefined profit function caused by the term $\ln(\alpha)$

when the retailer does not order anything (i.e., when he provides zero service level). Proposition 1 below characterizes the retailer's best response.

***Proposition 1.*** *The retailer's expected profit function has a unique local maximizer in the domain* $(0,\ \infty)$*. Let* $\alpha_i(t)$ *represent this local maximizer which is decreasing in the wholesale price* $w$*. The retailer's best response is*

$$\alpha^*(t) = \begin{cases} \alpha_{min}, & for\ \alpha_i(t) \leq\ \alpha_{min}, \\ \alpha_i(t), & for\ \alpha_i(t) \in (\alpha_{min}, 1), \\ 1, & for\ \alpha_i(t) \geq 1, \end{cases}$$

*if* $\prod_r(\alpha^*)\ \geq 0$ *holds. Otherwise, the retailer sets* $\alpha^*(t) =\ 0$.

For a given wholesale price $(w)$ and buyback price $(b)$, if the retailer's expected profit is nonnegative, the retailer's best response is to set his service level $\alpha$ either to the minimum service level $\alpha_{min}$, or to the local maximizer of the retailer's expected profit function $\alpha_i(t)$ or to 1.

The analysis of the retailer's problem under a wholesale contract follows parallel steps with the analysis explained above with the buyback price $b$ set equal to 0.

The retailer's best response service level α decreases in the manufacturer's wholesale price $w$ in the wholesale price contract model. A high wholesale price $w$ may force the retailer to offer the minimum service level and a very high wholesale price $w$ may force the retailer to set $\alpha^* =\ \alpha_o$ and to order zero units of product.

In the absence of the direct channel, all consumers visit the retailer as long as he provides at least the minimum service level $\alpha_{min}$. Thus, the retailer does not consider the effect of his service level decision on his demand and sets the critical fractile service level unless this level is below the minimum service level. Thus, under wholesale price contract, the following Corollary exists.

***Corollary 1.*** *If the manufacturer shuts down his direct channel by setting* $t\ \rightarrow \infty$*, then the retailer's best response is to set* $\lim_{t\rightarrow\infty} \alpha^*\ (t) = max\ \{\alpha_{min},\ (p-w)/p\}$.

### 3.3.2. Manufacturer's Problem

Here, we characterize the manufacturer's best response delivery lead time $t^*(\alpha)$ to the retailer's service level $\alpha$ choice. For a given buyback contract $(w, b)$, the manufacturer solves the following problem:

$$\max_t \prod_m(t) = (w-c)q + (p-c)E[D_d^1 + D_d^2] - b(q - E[\min\{D_r, q\}]) - \frac{m}{t^2}. \qquad (6)$$

In this function, the term $(w-c)$ denotes the unit profit margin of the manufacturer for the products that he sells to the retailer. The term $(p-c)$ denotes the unit profit margin of the manufacturer for the products that he sells to the consumers through the direct channel. The term $E[D_d^1 + D_d^2]$ denotes the total expected direct channel demand, which is a sum of the primary and the secondary demand. Because $b$ is equal to 0 under wholesale price contract, the term $(-b(q - E[\min\{D_r, q\}]))$ does not exist in the function under a wholesale price contract.

This function shows the manufacturer's trade-off between the two channels. The manufacturer makes a profit of $(p-c)$ for each unit sold in the direct channel and $(w-c)$ for each unit sold in the retail channel. Direct channel offers higher profit margin than the retail channel. However, with a wholesale price contract, the manufacturer carries no risk of sales in the retail channel because once he sells to the retailer; the retailer cannot return unsold products. The manufacturer considers this trade-off besides the cost of the direct channel while making channel decision.

Substituting the expected sales of the retailer $E[\min\{D_r, q\}]$ from Lemma 2 to Equation 6, the manufacturer's expected profit becomes

$$\max_t \prod_m(t) = \left(w - c - \frac{b\alpha}{2}\right) q + (p-c)E[D_d^1 + D_d^2] - \frac{m}{t^2}. \qquad (7)$$

Lemma 3 characterizes the expected sales in the direct channel and the manufacturer's expected profit function under a buyback contract.

***Lemma 3***. *The expected sales in the direct channel is* $E[D_d^1 + D_d^2] = (a/2)\left[\alpha(\alpha - 2)\big(d_2(\alpha) - d_1(\alpha)\big) + d_2(\alpha)\right]$. *The manufacturer's expected profit is a continuous function defined as*

$$
\prod_m(t) = \begin{cases} \prod_m^e(t) \equiv \frac{a}{2}(p-c) - \frac{m}{t^2}, & for\ t \le t^e, \\ \prod_m^a(t) \equiv a(w-c)\alpha + \frac{a(p-c)(1-\alpha)^2}{2} - \frac{ab\alpha^2}{2} + \frac{1}{t}G^a(\alpha) - \frac{m}{t^2}, & for\ t \in (t^e, v-p], \\ \prod_m^u(t) \equiv a(w-c)\alpha - \frac{ab\alpha^2}{2} + \frac{1}{t}\,G^u(\alpha) - \frac{m}{t^2}, & for\ t > v-p, \end{cases}
$$

*where* $G^a(\alpha) \equiv (a\alpha/2)\big[(v-p)\big(1-\alpha(1-\ln(\alpha))\big) + k\big][b\alpha + (p-c)(2-\alpha) - 2(w-c)]$ *and* $G^u(\alpha) \equiv [a(p-c)(1-\alpha)^2(v-p)]/2 + (a\alpha/2)\big[(v-p)\big(1-\alpha(1-\ln(\alpha))\big) + k\big][b\alpha + (p-c)(2-\alpha) - 2(w-c)]$.

The function above is defined with respect to the three delivery lead time domains of Lemma 1 (except the $t \to \infty$ case). When the manufacturer sets $t > v - p$, the direct channel cannot cover the whole consumer population $(i.e., d_2 < 1)$ and there is lost demand ("unaggressive case", denoted with superscript u). When the manufacturer sets $t \le v - p$, the direct channel covers the whole consumer population $(i.e., d_2 = 1)$ and there is no lost demand ("aggressive case", denoted with superscript a). The manufacturer can increase the market share of the direct channel by decreasing the delivery lead time below $v - p$. However, doing so will reduce the market share of the retail channel. At the extreme, the manufacturer can set $t \le t^e$ and eliminate the retailer (the first case in the lemma above). Lemma 4 below characterizes the profit functions $\prod_m^a(t)$ and $\prod_m^u(t)$.

***Lemma 4.***

*(i) The function* $\prod_m^a(t)$ *is increasing in* $t$ *when* $G^a(\alpha) \le 0$. *It is unimodal with a maximum at* $t_f^a = 2m/G^\alpha(\alpha)$ *when* $G^a(\alpha) > 0$.

*(ii) The function* $\prod_m^u(t)$ *is increasing in* $t$ *when* $G^u(\alpha) \le 0$. *It is unimodal with a maximum at* $t_f^u = 2m/G^u(\alpha)$ *when* $G^u(\alpha) > 0$.

*(iii) For* $\alpha = 1$, *we have* $\prod_m^u(t) = \prod_m^a(t)$.

*(iv) For* $\alpha < 1$, $\prod_m^a(t) = \prod_m^u(t)$ *only for* $t = v - p$. *We have* $\prod_m^u(t) > \prod_m^a(t)$ *for* $t < v - p$, *and* $\prod_m^a(t) > \prod_m^u(t)$ *for* $t > v - p$.

Lemmas 3 and 4 are used to characterize the manufacturer's best response function as shown in the following proposition.

***Proposition 2***. *Given the wholesale price $w$ and the buyback price $b$, the manufacturer's best response to the retailer's service level $\alpha$ choice is*

$$t^*(\alpha) = \begin{cases} t^e, & if\ G^a(\alpha) > 0\ and\ t_f^a \leq t^e, \\ t_f^a = \dfrac{2m}{G^a(\alpha)}, & if\ G^a(\alpha) > 0\ and\ t_f^a \in (t^e, v-p], \\ v-p, & if\ G^u(\alpha) > 0\ and\ t_f^u \leq v-p\ and\ \left(t_f^a > v-p\ or\ G^a(\alpha) \leq 0\right), \\ t_f^u = \dfrac{2m}{G^u(\alpha)}, & if\ G^u(\alpha) > 0\ and\ t_f^u > v-p, \\ \infty, & if\ G^u(\alpha) \leq 0. \end{cases}$$

The manufacturer's best response might be one of the five different delivery lead time types. At one extreme, the manufacturer may set $t = t^e$ and eliminate the retailer. In this case, the manufacturer will serve the whole consumer population through his direct channel. At another extreme, the manufacturer may set an arbitrarily long delivery lead time $t^* \to \infty$ and shut down the direct channel. In this case, the retailer will serve part of the consumer population depending on his service level. The other three types of delivery lead time types are between these extreme values. When the manufacturer sets $t^* = t_f^a$ (aggressive case) or $t^* = v - p$, both the direct and the retailer channels are operative. In these cases, the direct channel covers the whole consumer population and is an alternative for all consumers. When the manufacturer sets $t^* = t_f^u$ (unaggressive case), the direct channel satisfies part of the consumer demand, and some consumers may be lost.

### 3.3.3. The Nash Equilibrium

Next, we determine the Nash equilibrium of the operational decisions game between the manufacturer and the retailer for given contract parameters. To do so, we solve the best response functions characterized in Propositions 1 and 2 simultaneously. It is not possible to find a closed form solution due to the complexities of the best response functions. Thus, we use the following algorithm to determine the equilibrium numerically.

**The algorithm to determine the Nash equilibrium**

**Set** $\delta = 0.01,\ \in =\ 10^{-6}, \prod_m^* =$ (small number)

(Find the Nash equilibrium of the operational decisions game for a given $w$ and $b$)

***For*** $i = 1\ to\ i =$ number of initial seeds **Do**

**Set** $j = 0$ and $\alpha_j^* = (seed\ i)$ **and** $\alpha_{j+1} = t_{j+1}^* = t_j^* = (large\ number)$

**While** $\left(\alpha_{j+1}^* - \alpha_j^* > \epsilon\ and\ t_{j+1}^* - t_j^* > \in\right)$ **Do**

$t_{j+1}^*(\alpha_j^*) \leftarrow$ (find the manufacturer's best response to $\alpha_j^*$),

$\alpha_{j+1}^*(t_{j+1}^*) \leftarrow$ (find the retailer's best response to $t_{j+1}^*$)

$j \leftarrow j + 1$ (increment j by one)

**End While**

**Report** the Nash equilibrium as the pair $\left(\alpha_j^*(i), t_j^*(i)\right)$

**End For** $i$ loop

**Report** $\prod_m^*$, and the corresponding $(t^*, \alpha^*)$.

The algorithm stated above is an application of the *best response dynamics* methodology (Matsui, 1992). The algorithm finds the pure strategy Nash equilibrium $(t^*, \alpha^*)$ iteratively. In each iteration, the algorithm determines the manufacturer's best response $t$ value and the retailer's best response $\alpha$ value to the current action of the other party. The algorithm runs until a joint strategy is reached from which neither the manufacturer nor the retailer has an incentive to deviate. Note that theory does not guarantee the uniqueness of the Nash Equilibrium. However, we did not observe any multiple equilibrium case when this algorithm was run starting with 10 different α seed values in (0, 1] domain.

### 3.4. Stage I: Contracting

In order to find the manufacturer's optimal buyback contract parameters $(w, b)$, we conducted a grid search over the wholesale price values $w \in [c, p]$ and the buyback price values $b \in [0, w]$. The selection rule is to choose the $(w, b)$ pair, which maximizes the manufacturer's expected profit for the Nash equilibrium found at stage II.

So far, we explained how we solved the three-stage game with backwards induction. Next, we outline how we proceed afterwards.

### 3.5. Solution Methodology

The manufacturer's optimal wholesale price $w$ and buyback price $b$ that are found by backwards induction are used to determine the manufacturer's delivery lead time $t$ and the retailer's service level $\alpha$ decisions at stage II. Then, the expected profits of the firms and sales of the channels are obtained at stage III. We coded this solution procedure, including backwards induction steps, in Matematica to determine the solution for a given parameter set $(v,\ p,\ k,\ c,\ m)$ automatically. We fixed the value of the parameter $a$ to 1000, without loss of generality[2].

The core of the Mathematica code is the algorithm described in Section 3.3.3. This algorithm is used to find the Nash equilibrium of the stage II game for given contract parameter $(w, b)$ values. The code determines the Nash equilibrium for all possible contract parameter $(w, b)$ values in a nested grid, and then chooses the optimal contract parameter $(w, b)$ values for the manufacturer. The code stores the solution that consists of the contract parameter $(w, b)$ values, the resulting operational decisions in the Nash equilibrium, and the expected sales quantities in each channel and the expected profits of the firms.

In order to analyze the effect of the five parameters of the model $(v,\ p,\ k,\ c,\ m)$, the model is solved with all combinations of these parameters' low, medium and high values as shown in Table 3.1. Hence, the model is solved $3^5 = 243$ times, each time covering a different dual channel environment through the choice of the five parameter values.

Table 3.1. Low, Medium and High Values of Parameters

| $m$ | $v$ | $p/v$ | $k/(v-p)$ | $c/p$ |
|---|---|---|---|---|
| 1000 | 4 | 0.25 | 0.125 | 0 |
| 5000 | 8 | 0.5 | 0.5 | 0.25 |
| 10000 | 12 | 0.75 | 0.75 | 0.5 |

[2] What matters for the model is the ratio between the two parameters "$a$" and "m". Hence, the model only has five independent parameters.

Note that the $m$ and $v$ values are absolute, whereas the $p$, $k$ and $c$ values are chosen relatively. This is because of the constraints $p < v,\ k \leq v - p$ , and $c < p$.

### 3.6. Main Findings

We present our main findings in three parts. First, we show that there are three types of equilibrium. Second, we illustrate how the manufacturer's optimal dual channel strategy changes with respect to the changes in the values of the parameters. Third, we illustrate how the values of the decision variables change when the manufacturer switches from one dual channel strategy to another.

#### 3.6.1. Partition into Three Equilibrium Regions

The results of our numerical studies suggest that the five-dimensional parameter space is divided into three *equilibrium regions*. Each region implies an optimal *dual channel strategy* for the manufacturer. These three types of equilibrium are as follows:

- *Eliminate Retailer (ER)*: In this equilibrium type, the manufacturer eliminates the retailer by setting a high wholesale price $w$ (in comparison to the sales price $p$) and a short delivery lead time $t$. With a buyback contract, he also sets a low buyback price $b$. The retailer sets zero stocking quantity $q$ and leaves the market. We have $d_1 = d_2 = 1$; hence, there is only one consumer segment, which is covered by the manufacturer's direct channel.

- *Capture All Profit (CP)*: In this equilibrium type, the manufacturer sells through both channels; however, captures all profit from the retailer. To do so, he sets a wholesale price $w$ (and a buyback price $b$ in the buyback contract case) such that the retailer makes almost no profit. The retailer's minimum availability constraint is binding (i.e., he sets $\alpha_{min}$). We have $d_1 = d_2 < 1$ and the consumers are partitioned into two segments.

- *Share Profit (SP)*: In this equilibrium type, the manufacturer uses both the direct and the retail channel and shares the profit with the retailer. The manufacturer sets a low wholesale price $w$ (in comparison to the sale price $p$) with a wholesale price contract; a high wholesale price $w$ and a high buyback price $b$ with a buyback contract. By doing so, the manufacturer lets the retailer have positive profit margin. We have, $d_1 < d_2 < 1$ and the consumers are partitioned into three segments.

Note that given a dual channel environment, which is described by the five model parameters, the manufacturer can change the type of the resulting equilibrium (i.e., his optimal dual channel strategy) by changing the value of contract parameters $(w, b)$ at stage I. Each equilibrium type is associated with a different combination of market segmentation, channel configuration, and profit sharing strategy.

Table 3.2 provides a sample of numerical results from the wholesale price contract model. The manufacturer's optimal wholesale price $w^*$, the Nash equilibrium decisions $t^*$ and $\alpha^*$, the expected profits of the firms, the expected sales in each channel, and the manufacturer's optimal dual channel strategy type ("Eql. Type") are shown for given parameter combinations.

Table 3.2. Sample Results from the Wholesale Price Contract Model

| **Parameters** | | | | | **Decision Variables** | | | **Profits** | | **Sales** | | | **Eql. Type** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $m$ | $v$ | $p$ | $k$ | $c$ | $w^*$ | $t^*$ | $\alpha^*$ | $\prod_m$ | $\prod_r$ | Direct | Retail | Lost | |
| 1000 | 4 | 1 | 0.38 | 0.00 | 1.00 | 3.00 | 0.03† | 389 | 0 | 500 | 0 | 0 | ER |
| 1000 | 12 | 3 | 4.50 | 0.75 | 2.73 | 9.00 | 0.19† | 1113 | 0 | 500 | 0 | 0 | ER |
| 5000 | 12 | 6 | 3.00 | 3.00 | 5.44 | 6.00 | 0.19† | 1361 | 0 | 500 | 0 | 0 | ER |
| 1000 | 4 | 2 | 1.00 | 1.00 | 1.80 | 2.85 | 0.19 | 272 | 1 | 351 | 51 | 99 | CP |
| 5000 | 4 | 3 | 0.75 | 1.50 | 2.42 | 25.11 | 0.38 | 360 | 2 | 20 | 297 | 183 | CP |
| 10000 | 8 | 6 | 1.50 | 1.50 | 4.84 | 10.28 | 0.38 | 1372 | 4 | 97 | 249 | 154 | CP |
| 5000 | 4 | 1 | 0.38 | 0.50 | 0.77 | 19.85 | 0.24 | 77 | 24 | 61 | 191 | 248 | SP |
| 5000 | 8 | 6 | 1.00 | 0.00 | 3.72 | 3.90 | 0.43 | 1923 | 271 | 206 | 214 | 80 | SP |
| 10000 | 4 | 3 | 0.50 | 0.75 | 1.89 | 31.30 | 0.37 | 435 | 200 | 14 | 296 | 191 | SP |

† $d_1(\alpha^*) \equiv 1$; hence $q^* = 0$.

Similarly, Table 3.3 provides sample results from the buyback contract model.

Table 3.3. Sample Results from the Buyback Contract Model

| Parameters | | | | | Decision Variables | | | | Profits | | Sales | | | Eql. Type |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $m$ | $v$ | $p$ | $k$ | $c$ | $w^*$ | $b^*$ | $t^*$ | $\alpha^*$ | $\prod_m$ | $\prod_r$ | Direct | Retail | Lost | |
| 1000 | 12 | 3 | 4.50 | 0.75 | 2.75 | 0.00 | 9.00 | 0.19 | 1113 | 0 | 500 | 0 | 0 | ER |
| 5000 | 12 | 6 | 3.00 | 3.00 | 5.45 | 0.00 | 6.00 | 0.19 | 1361 | 0 | 500 | 0 | 0 | ER |
| 10000 | 12 | 3 | 1.13 | 1.50 | 3.00 | 0.00 | 9.00 | 0.03 | 627 | 0 | 500 | 0 | 0 | ER |
| 1000 | 4 | 2 | 1.50 | 1.00 | 2.00 | 2.00 | 3.79 | 0.38 | 306 | 0 | 264 | 146 | 90 | CP |
| 5000 | 8 | 4 | 3.00 | 2.00 | 3.55 | 1.65 | 4.74 | 0.38 | 695 | 0 | 422 | 48 | 30 | CP |
| 10000 | 8 | 2 | 4.50 | 1.00 | 2.00 | 2.00 | 12.63 | 0.38 | 299 | 0 | 237 | 162 | 101 | CP |
| 1000 | 4 | 2 | 1.00 | 1.00 | 1.95 | 1.85 | 3.94 | 0.38 | 291 | 5 | 216 | 189 | 95 | SP |
| 5000 | 4 | 3 | 0.75 | 1.50 | 2.95 | 2.90 | 27.21 | 0.50 | 369 | 12 | 17 | 364 | 119 | SP |
| 10000 | 8 | 6 | 1.50 | 1.50 | 5.90 | 5.85 | 18.52 | 0.68 | 1667 | 30 | 45 | 409 | 47 | SP |

### 3.6.2. The Manufacturer's Optimal Dual Channel Strategy

Next, we illustrate how the manufacturer's optimal dual channel strategy (*ER, SP* or *CP*) changes with respect to the changes in the values of the five model parameters. In our numeric experiments with the wholesale price contract, we observed that when the level of a parameter increases, the manufacturer's policy changes at most twice, in a given sequence. For instance, as the value of the direct channel cost parameter $m$ increases, the manufacturer's optimal policy changes from *ER* to *SP* to *CP*. The policy does not switch from *SP* to *ER* or from *CP* to *ER* or from *CP* to *SP***.** Figure 3.3 summarizes these observations for all five parameters. We note that high values of the direct channel cost $m$, sales price $p$, search cost $k$ and unit production cost $c$ motivate the manufacturer towards the *CP* policy, whereas high customer valuation $v$ motivates the manufacturer towards *ER* policy. The direction from *ER* to *CP* also indicates increasing use of the retail channel by the manufacturer.

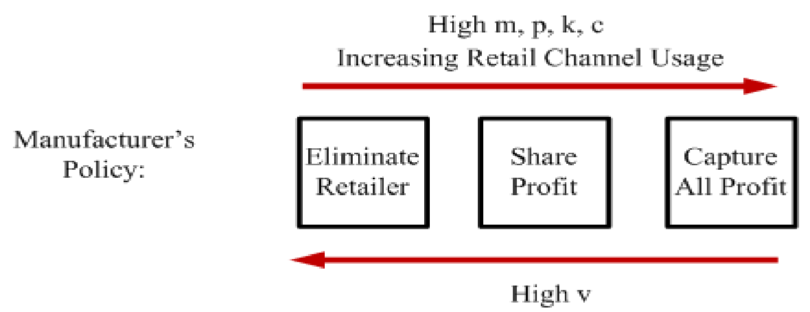



Figure 3.3. Changes in the Manufacturer's Optimal Channel Policy with the WPCM

Next, we provide more details on the manufacturer's optimal policy, focusing on the direct channel cost parameter $m$ and the retailer inconvenience cost parameter $k$ as examples. Table 3.4 shows how the manufacturer's optimal dual channel strategy changes within this parameter space in the wholesale price contract model. We obtain structurally similar results in the buyback contract model as well.

Table 3.4. Manufacturer's Optimal Channel Strategy in the WPCM, when $v$ = 8, $p$ = 4, $c$ =1

| $m/k$ | 0.00 | 0.25 | 0.50 | 0.75 | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 | 2.75 | 3.00 | 3.25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **20000** | SP | SP | SP | SP | SP | SP | SP | SP | SP | SP | CP | CP | CP | CP |
| **17500** | SP | SP | SP | SP | SP | SP | SP | SP | SP | SP | CP | CP | CP | CP |
| **15000** | SP | SP | SP | SP | SP | SP | SP | SP | SP | SP | CP | CP | CP | CP |
| **12500** | SP | SP | SP | SP | SP | SP | SP | SP | SP | SP | CP | CP | CP | CP |
| **10000** | ER | ER | ER | ER | SP | SP | SP | SP | SP | SP | CP | CP | CP | CP |
| **7500** | ER | ER | ER | ER | ER | ER | ER | ER | ER | SP | CP | CP | CP | CP |
| **5000** | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | CP |
| **2500** | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER |
| **0** | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER | ER |

As seen in Table 3.4, $m/k$ plane is divided into three strategy regions. If both the direct channel cost $m$ and the retailer inconvenience cost $k$ are high, the manufacturer's optimal dual channel strategy is capture-all-profit (*CP*). The manufacturer is aware of the retailer's high inconvenience cost, which denotes a high minimum service level $\alpha_{min}$ at the retailer. Recall that to stay in business; the retailer has to set at least the minimum service level. Thus, the manufacturer sets a high wholesale price (enough to provide the minimum expected profit for the retailer) and captures all profit from the retailer. If the direct channel cost $m$ is high and the retailer's inconvenience cost $k$ is low, the manufacturer's optimal dual channel strategy is share-profit (*SP*). As the manufacturer has a cost disadvantage at the direct channel, he prefers not increasing the wholesale price a lot and leaves some profit to the retailer. If the direct channel cost $m$ is low, the manufacturer's optimal dual channel strategy is eliminate-retailer (*ER*).

Figure 3.4 illustrates the partitioning of the $m/k$ plane into the three equilibrium regions. The figure also shows how the other three model parameters (the unit production cost $c$, selling price $p$, and consumer valuation $v$) affect the boundaries between these three regions. For example, decreasing the unit production cost $c$ and the selling price $p$ increases the eliminate-retailer ($ER$) region. For given values of these three other parameters, it is possible that the $m/k$ plane is covered by only one or two of these three regions.

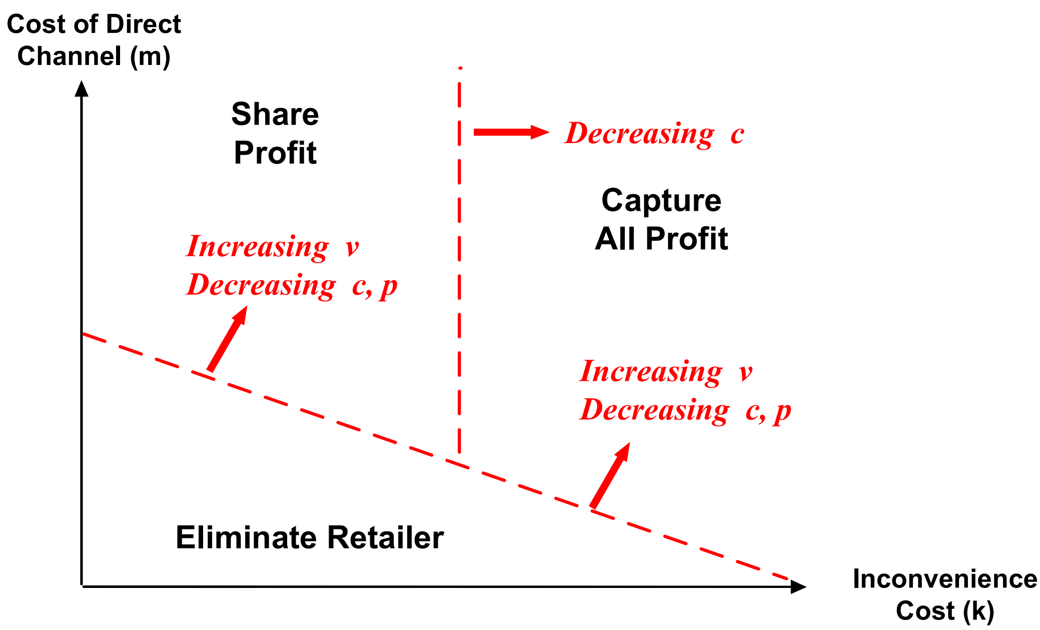



Figure 3.4. Manufacturer's Optimal Dual Channel Strategy on $m/k$ Plane in the WPCM

### 3.6.3. Effects of Parameters on the Decision Variables and Resulting Profits

The following figure illustrates how the changes in a particular parameter ($k$, as an example) leads to changes in the equilibrium values of the decision variables $\{w, \alpha, t\}$ for given values of the other four parameters, in the wholesale price contract model. Figure 3.5 also illustrates how the manufacturer's optimal dual channel strategy changes as k increases.

When the retailer's inconvenience cost is low, the retail channel becomes a strong competitor to the direct channel. Thus, the manufacturer eliminates the retailer by setting a short delivery lead time and a high wholesale price. When the retailer's inconvenience cost is moderate, the retailer increases his service level to meet the consumer demand. As a result, the manufacturer increases the delivery lead time and reduces the wholesale price to collaborate with the retailer. When the retailer's inconvenience cost is high, the retailer's minimum service level constraint is binding. Hence, the retailer selects $\alpha_{min}$ as his service level, and the manufacturer, who knows this fact, increases the delivery lead time to shift the sales to the retail channel. While doing so, however, the manufacturer captures all profit and leaves the retailer with (almost) zero profit.

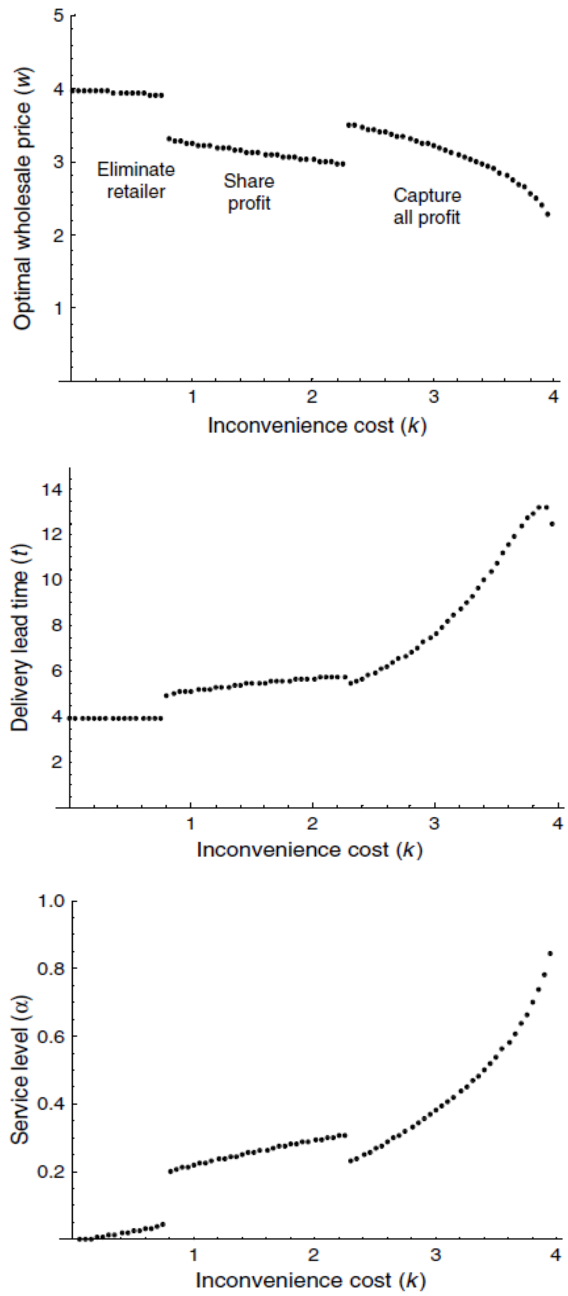



Figure 3.5. Decision Variables in Equilibrium in the WPCM
Note. $m = 10{,}000,\ v = 8,\ p = 4,\ c = 1.$

As illustrated in Figure 3.6, changes in the dual channel strategies also affect the expected sales of the channels and the profits of the firms. The manufacturer's profit is stable for any value of the inconvenience cost under a threshold, because the retailer is eliminated. When the strategy switches to share-profit (i.e., the inconvenience cost is higher than this threshold), the manufacturer's profit starts to increase. The manufacturer's profit increases rapidly when the retailer's inconvenience cost is high (i.e., when the strategy is capture-all-profit). In the expected sales figures, we observe that when the strategy is eliminate-retailer, the manufacturer meets all consumer demand. However, the retailer makes moderate amount of sales when the strategy is share-profit. In the capture-all-profit strategy, the retailer increases his sales due to increased delivery lead time in the direct channel; however, he gains almost no profit.

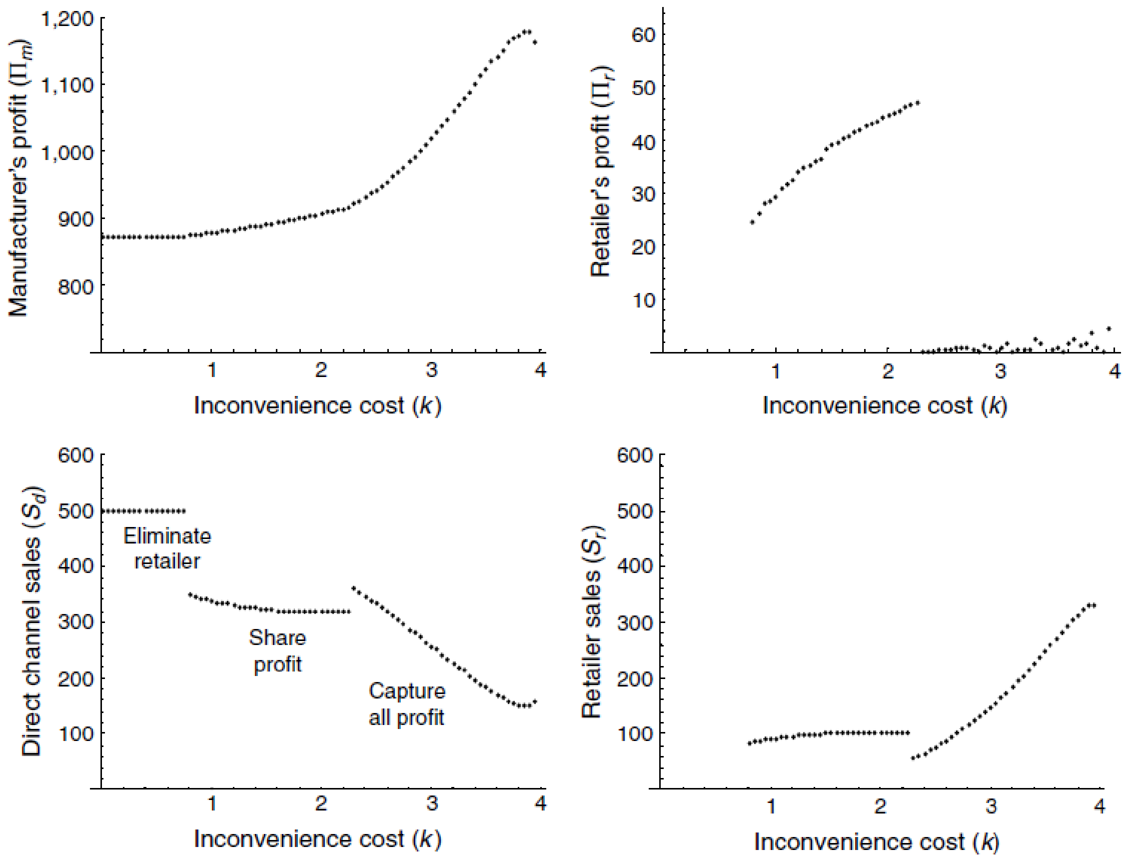



Figure 3.6. Expected Profits and Sales in the WPCM
Note. $m = 10{,}000,\ v = 8,\ p = 4,\ c = 1.$

### 3.6.4. Comparison of the Wholesale Price and Buyback Contract Models

Here, we compare the results of the wholesale price contract model (WPCM) and the buyback contract model (BCM). As seen in Table 3.5, we only present the profit comparisons for selected $m$ and $c$ values.

Table 3.5. Expected Profits under Different Contract Types
Note. $v$ = 8, $p$ = 4, $k$ =1.

| **Parameters** | | **Manufacturer's Profit** | | **Retailer's Profit** | | **Total System Profit** | |
|---|---|---|---|---|---|---|---|
| $m$ | $c$ | WPCM | BCM | WPCM | BCM | WPCM | BCM |
| 5000 | 0 | 1687.5 | 2000 | 0 | 0 | 1687.5 | 2000 |
| 5000 | 1.25 | 1062.5 | 1062.5 | 0 | 0 | 1062.5 | 1062.5 |
| 5000 | 3.25 | 130.07 | 137.81 | 0.46 | 1.82 | 130.53 | 139.62 |
| 12500 | 0 | 1255.87 | 2000 | 145.68 | 0 | 1401.56 | 2000 |
| 12500 | 1.25 | 704.8 | 930.28 | 73.58 | 31.75 | 778.38 | 962.03 |
| 12500 | 3.25 | 76.4 | 94.01 | 0.78 | 3.55 | 77.18 | 97.56 |
| 22500 | 0 | 1134.24 | 2000 | 316.59 | 0 | 1451.32 | 2000 |
| 22500 | 1.25 | 599.24 | 922.24 | 151.14 | 32.43 | 750.38 | 954.67 |
| 22500 | 3.25 | 60.5 | 81.32 | 0.87 | 3.82 | 61.37 | 85.14 |

We observe that in terms of total system and manufacturer's profit, BCM outperforms WPCM in all parameter combinations except one. This is expected because WPCM is a special case of BCM. We observe that the retailer's profit is usually higher under the wholesale price contract. This is because the buyback contract gives more control to the manufacturer (i.e., two contract parameters to set).

# CHAPTER 4

## CHAPTER 4 : EXPERIMENTAL STUDY OF WHOLESALE PRICE CONTRACT MODEL

In this chapter, we explain and analyze the experimental study that we conducted on our wholesale price contract model (WPCM). First, we provide information on the experimental procedure and design. Second, we focus on the analysis of the experimental data.

### 4.1. Experimental Procedure and Design

Our experiments were computer-based and conducted at the HP Experimental Economics Laboratory in Palo Alto, CA. The experimental model was implemented in MUMS, the special-purpose script language developed by HP Laboratories. Subjects were selected from the Stanford University students. Instructions for the experiments and a quiz for training were provided on the web[3]. Only the subjects who passed this web-based quiz were allowed to participate in the experiments. This helped to reduce the training time of the subjects before the experiments and filtered them according to their understanding of the experimental logic. During the experimental studies, subjects were seated at computer carrels separated from each other by dividers. A monetary reward was paid to each subject according to his success in the experiments. A certain percentage of each subject's experimental payoff was transformed into his monetary reward and added to the 25$ participation fee. The average monetary reward was around 70$.

We conducted 17 experiments in 7 sessions. Each session lasted around 2.5 hours. The same subject set was used for all experiments of a session. Before beginning each

[3] See http://www.hpl.hp.com/econexperiment/dual-channel/ for the instructions and quiz.

session, an experimenter explained the details of the game and answered the questions of the subjects. The subjects were allowed to play several training periods before the session started. The subjects were informed when a new experiment started (i.e., when a different parameter set was used). In each experiment, the same game was played for 25-40 independent periods. At the beginning of each period, each subject was randomly matched with another subject. Subjects did not know with whom they were matched. A subject from each pair was randomly selected as manufacturer and the other as the retailer. Participating in both roles helped the subjects to understand the whole game, which is consistent with the full information assumption of the analytical model. Moreover, a specific subject played the role of the manufacturer and the retailer in equal number of times, which led to a fair distribution of monetary rewards. This is because the expected payoff of the manufacturer and the retailer are not equal in an experiment. At the end of each session, the subjects were paid according to their performance.

A period in an experiment consisted of three stages, in general. At stage I, the manufacturer set the wholesale price between the integer values 1 to price $p$[4]. At stage II, given the wholesale price, the manufacturer decided on the delivery lead time, and the retailer decided on the stock level simultaneously[5]. At stage III, a random number of consumers were created by the server computer, so that the demand in each channel and the profit of each channel member were realized. In some of the experiments, the periods started directly from stage II, assuming an exogenously-given wholesale price. At each stage, 45 seconds were given to the subjects to make decisions.

We provided a decision support tool in subjects' screens during the experiments. By using this tool, the subjects could run what-if analysis before submitting their decisions. For instance, the retailer subject could enter a stocking level and his guess on the manufacturer subject's delivery lead time to this tool, and obtain the results for 11 different realizations of the random total market demand ($X = 0, 100, 200 \ldots 1000$). Subjects entered their decisions into the box at the bottom of the screens. At the end of each period, the subjects learned total demand realization, operational decision of his counterpart, number of units sold in each channel, number of lost customers, and his

[4] We constrained the wholesale price decisions to integer values to facilitate the decision-making process of subjects and our analysis.

[5] In our experiments, we used the stocking level $q$, which is indeed equal to the service level $\alpha$, for the retailer's service level. Because setting stocking level is more intuitive than setting service level for human subjects. The delivery lead time decision is not restricted to be an integer; however, the stocking level decision is.

profit in the period. In addition, a historical results page was provided to every subject, presenting all previous periods' results for that subject.

Table 4.1 shows the experimental design for sessions 1 to 3. All experiments in these sessions start from stage II, assuming an exogenously given wholesale price. In each session, there are three experiments, which differ in the optimal dual channel strategy of the manufacturer. In other words, the experimental parameters were selected such that the theoretical outcome of the each experiment refers to one of the three optimal dual channel strategies.

Table 4.1. Experimental Design for Sessions 1-3

| Session | # Subjects | Exp. | # Periods | Equilibrium Type | Experiment Type | k | m | w | v | p |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 10 | 1a | 25 | Share Profits | given-w | 3 | 100,000 | 4 | 20 | 10 |
| | | 1b | 25 | Capture Profits | given-w | 8 | 500,000 | 6 | 20 | 10 |
| | | 1c | 25 | Eliminate Retailer | given-w | 8 | 5,000 | 8 | 20 | 10 |
| 2 | 10 | 2a | 30 | Share Profits | given-w | 3 | 100,000 | 4 | 20 | 10 |
| | | 2b | 25 | Capture Profits | given-w | 8 | 500,000 | 6 | 20 | 10 |
| | | 2c | 25 | Eliminate Retailer | given-w | 8 | 5,000 | 8 | 20 | 10 |
| 3 | 8 | 3a | 25 | Share Profits | given-w | 2 | 50,000 | 2 | 10 | 6 |
| | | 3b | 25 | Capture Profits | given-w | 3 | 200,000 | 4 | 10 | 6 |
| | | 3c | 25 | Eliminate Retailer | given-w | 3 | 5,000 | 5 | 10 | 6 |

Table 4.2 shows the experimental design for sessions 4 to 7. All of these sessions include two types of experiments: (1) A w-setting experiment where the manufacturer sets the wholesale price at stage I (experiments 4a, 5a, 6a and 7a); (2) A given-w experiment where the theoretical optimal wholesale price is exogenously given and the game starts from stage II (experiments 4b, 5b, 6b and 7b).

Table 4.2. Experimental Design for Sessions 4-7

| Session | # Subjects | Exp. | # Periods | Equilibrium Type | Experiment Type | k | m | v | p |
|---|---|---|---|---|---|---|---|---|---|
| 4 | 14 | 4a | 35 | Share Profits | w-setting | 2 | 100,000 | 10 | 6 |
| | | 4b | 30 | Share Profits | given-w as 3 | 2 | 100,000 | 10 | 6 |
| 5 | 8 | 5a | 35 | Share Profits | w-setting | 2 | 100,000 | 10 | 6 |
| | | 5b | 30 | Share Profits | given-w as 3 | 2 | 100,000 | 10 | 6 |
| 6 | 10 | 6a | 40 | Capture Profits | w-setting | 8 | 200,000 | 15 | 6 |
| | | 6b | 25 | Capture Profits | given-w as4 | 8 | 200,000 | 15 | 6 |
| 7 | 10 | 7a | 35 | Eliminate Retailer | w-setting | 0 | 10,000 | 10 | 6 |
| | | 7b | 30 | Eliminate Retailer | given-w as 6 | 0 | 10,000 | 10 | 6 |

## 4.2. Analysis of the Experimental Data

We present the analysis of the experimental data in three parts. First, we provide a general view of the results after eliminating the outliers. Second, we provide our analysis related to stage II decisions. This part covers the comparison of the equilibrium predictions with observed data, learning in the operational decisions game, and the effect of experiment type or wholesale price on the operational decisions. Third, we focus on the decisions at stage I where the manufacturer sets the wholesale price. In this part, we compare the theoretical optimum predictions with observed data and analyze learning in the wholesale price decisions.

We used the term "theoretical predictions" to express the model's predictions. We used non-parametric tests, as we had no prior assumptions on the distributions of the assessed variables. We mostly used the Kolmogrov-Smirnov test, the Wilcoxon Signed-Rank test and the Wilcoxon Rank-Sum test (the Mann-Whitney U test) to test the significance of our results. We also implemented a two-dimensional Kolmogrov-Smirnov test based on the algorithm of Press et al. (1992). The algorithm is provided in Appendix B.

### 4.2.1. General View of the Data

First, we eliminated outliers from our data. In statistics, an outlier is a numerically distant observation from the rest of the data. One reason why outliers existed in our data is that the subjects had mistaken their roles. Recall that in each period, the roles were re-assigned: a manufacturer subject might become a retailer in a subsequent period or vice versa. For instance, in experiment 4b, some manufacturer subjects set very high delivery lead times such as 400, 550, 1000 when the average delivery lead time was around 27, because they were making decisions as if they were determining the stock level being retailers. On the other hand, in some occasions, manufacturer subjects set extremely low delivery lead time values such as 0 or 1, when the average delivery lead time was around 27. We eliminated such cases from our data as well. In total, we eliminated 22 data from our experiment results. Eliminated outlier data is presented in Appendix C. We conducted all statistical tests after these eliminations. We used a significance level of 0.05 for the statistical analysis.

Table 4.3 provides the results on delivery lead time $t$, stocking level $q$, manufacturer's profit and retailer's profit in each experiment. We show the model's theoretical predictions under column "Eql." (equilibrium) and mean of the observed data under column "Avg." (average). In Table 4.4, for the w-setting experiments (i.e., 4a, 5a, 6a and 7a), we also provide the results related to the cases in which the manufacturer subjects set the theoretical-optimal wholesale price at stage I.

Table 4.3. General View of the Results

| | | | **Delivery Lead Time $t$** | | **Stock Level $q$** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Eql. Type | Exp. Type | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| 1a | SP | w-given as 4 | 13.95 | 16.35 | 495.44 | 364.79 | 3015.93 | 2837.77 | 1315.17 | 1096.94 |
| 1b | CP | w-given as 6 | 23.55 | 25.44 | 258.29 | 253.10 | 2761.47 | 2571.10 | 456.26 | -136.85 |
| 1c | ER | w-given as 8 | 10.00 | 10.82 | 0.00 | 45.42 | 4950.00 | 5035.26 | 0.00 | -239.87 |
| 2a | SP | w-given as 4 | 13.95 | 18.36 | 495.44 | 393.97 | 3015.93 | 3013.03 | 1315.17 | 1198.81 |
| 2b | CP | w-given as 6 | 23.55 | 29.83 | 258.29 | 238.01 | 2761.47 | 2415.41 | 456.26 | -79.59 |
| 2c | ER | w-given as 8 | 10.00 | 9.79 | 0.00 | 21.26 | 4950.00 | 4932.18 | 0.00 | -119.23 |
| 3a | SP | w-given as 2 | 15.67 | 17.49 | 593.40 | 476.46 | 1439.73 | 1182.20 | 1143.39 | 1025.25 |
| 3b | CP | w-given as 4 | 34.32 | 46.49 | 337.83 | 355.76 | 1531.19 | 1423.98 | 288.10 | -9.61 |
| 3c | ER | w-given as 5 | 4.00 | 11.91 | 0.00 | 108.18 | 2687.50 | 2225.36 | 0.00 | -236.64 |
| 4a | SP | w-setting | 24.56 | 26.86 | 461.12 | 358.05 | 1572.83 | 1271.81 | 670.82 | 507.20 |
| 4b | SP | w-given as 3 | 24.56 | 26.71 | 461.12 | 390.00 | 1572.83 | 1359.59 | 670.82 | 617.55 |
| 5a | SP | w-setting | 24.56 | 28.09 | 461.12 | 368.12 | 1572.83 | 1256.37 | 670.82 | 593.73 |
| 5b | SP | w-given as 3 | 24.56 | 27.25 | 461.12 | 350.44 | 1572.83 | 1271.12 | 670.82 | 571.74 |
| 6a | CP | w-setting | 18.34 | 17.77 | 288.91 | 288.98 | 2033.24 | 1396.11 | 86.12 | 133.59 |
| 6b | CP | w-given as 4 | 18.34 | 16.77 | 288.91 | 142.85 | 2033.24 | 1455.73 | 86.12 | -84.07 |
| 7a | ER | w-setting | 4.00 | 13.98 | 0.00 | 278.70 | 2375.00 | 1925.59 | 0.00 | 265.76 |
| 7b | ER | w-given as 6 | 4.00 | 5.21 | 0.00 | 2.82 | 2375.00 | 2137.58 | 0.00 | 0.08 |

From the table above, we observe that the stage II decisions are close to the equilibrium values. However, in general, manufacturers set longer delivery lead times than the model's prediction, and retailers set lower stocking levels than the model's prediction when the predicted level is high and higher stocking levels than the model's prediction when the predicted level is zero.

Table 4.4. Observed Results for Theoretical Optimal w in w-setting Experiments

| | | | | **Delivery Lead Time $t$** | | **Stock Level $q$** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Eql. Type | Explanation | # of Data | Eql | Avg. | Eql | Avg. | Eql | Avg. | Eql | Avg. |
| 4a | SP | w = 3 data | 121 | 24.56 | 27.42 | 461.12 | 389.85 | 1572.83 | 1317.99 | 670.82 | 548.53 |
| 5a | SP | w = 3 data | 102 | 24.56 | 29.80 | 461.12 | 353.59 | 1572.83 | 1239.00 | 670.82 | 475.41 |
| 6a | CP | w = 4 data | 17 | 18.34 | 18.47 | 288.91 | 119.41 | 2033.24 | 1115.88 | 86.12 | -226.00 |
| 7a | ER | w = 6 data | 3 | 4.00 | 7.67 | 0.00 | 0.33 | 2375.00 | 1263.00 | 0.00 | 0.00 |

Next, we discuss our observations in detail.

### 4.2.2. Results in the Stage II Decisions

Here, we focus on the operational decisions game at stage II. We aim to determine whether Nash Equilibrium is a good predictor of the operational decisions game outcome, whether there exists any learning in the operational decisions over time, and whether experiment type or wholesale price affects operational decisions. In the following three subsections, for the given-w experiments, we consider all data, whereas for w-setting experiments, we only consider the data in which the manufacturer subjects set the theoretical optimal wholesale price at stage I.

#### 4.2.2.1. Comparing the Equilibrium Predictions and Observed Data

Here we analyze if Nash equilibrium is a good predictor of the operational decisions game results at stage II.

In each of sessions 1-3, the subjects' decisions in one experiment deviated significantly from their decisions in another experiment. We supported these separation results by the two-dimensional Kolmogrov-Smirnov tests with extremely low p-values in all comparisons (p-values < $10^{-6}$). Our theoretical predictions on sessions 1, 2 and 3 are such that the manufacturer's delivery lead time $t$ in experiment a will be lower than in experiment b, but will be higher than that in experiment c; and the retailer's stocking level $q$ in experiment b will be higher than that in experiment c, but lower than that in experiment a in a given session.

When we analyze our results, we see that directional changes in the experiment results are consistent with the model's predictions. The average values of subjects' decisions in each experiment reflect these comparisons. Figure 4.1 shows this result for session 2. In the figure, we compare the observed results in one experiment with another. Each triangle or circle in the figure shows the outcome of one game played between a manufacturer and a retailer couple in a given experiment. Squares represent the theoretical Nash equilibrium of each experiment. It is seen from the figure that the decisions in one experiment are separated from the decisions in other experiment in the predicted directions. Hence, the directional predictions of the model appear to be robust with respect to behavioral issues. Thus, qualitative recommendations of the model are likely to be implemented in actual business environments.

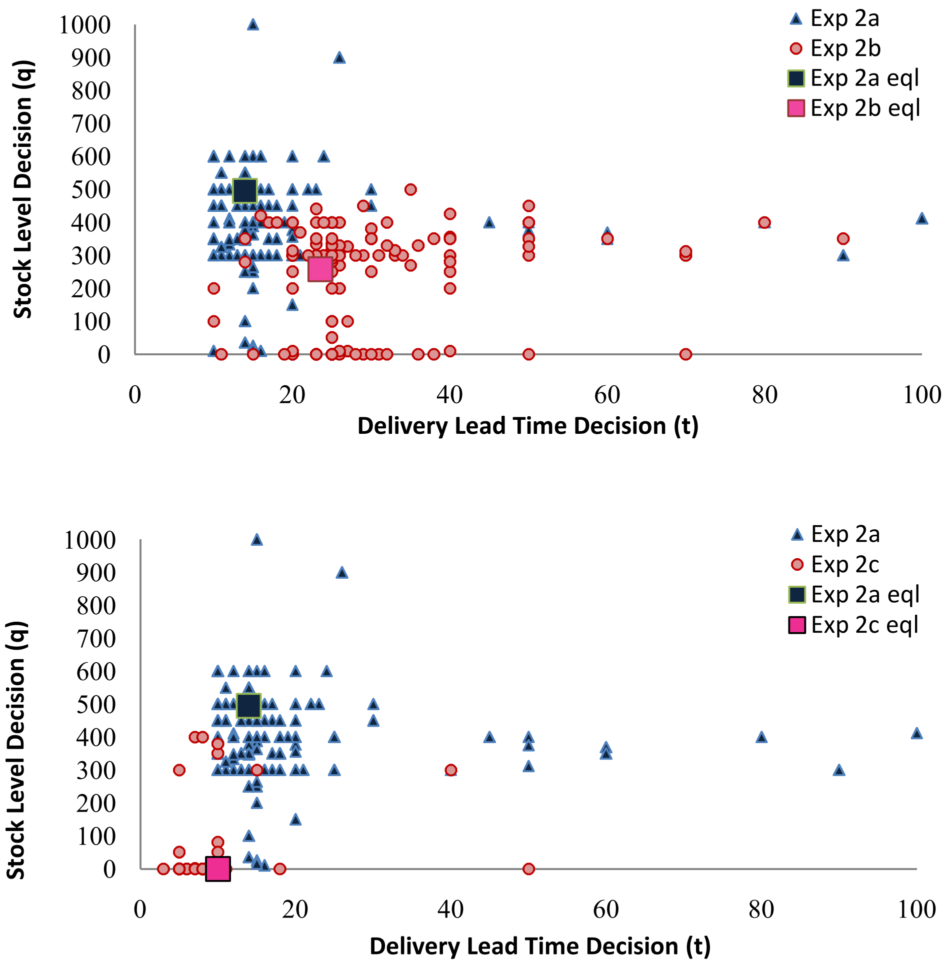



Figure 4.1. Decisions in Session 2

Moreover, each experiment's results are consistent with the characteristics of the predicted equilibrium type. These can be observed in Table 4.3 presented above. For instance, consider experiment 2c in session 2. Given the experimental setup, the analytical model predicts that the manufacturer's optimal dual channel strategy will be Eliminate Retailer, $ER$. Thus, he will set a very short delivery lead time and the retailer will order zero stocking quantity. This is how the subjects behaved, on average. The manufacturer subjects' average delivery lead time $t$ is even shorter than predicted and the retailer subjects' average stocking level $q$ is close to zero. When we checked the subjects' stocking level decisions, we observed that they chose zero stocking level in a significant number of periods in experiment 2c and are eliminated from the market. However, in some periods, the retailer subjects chose a positive stocking quantity leading to a loss, which caused a negative average profit of retailer in experiment 2c.

Although the model's qualitative predictions hold, the data exhibits deviations from the model's quantitative equilibrium predictions. Table 4.5 shows the predicted equilibrium values (in the Eql. column), mean values of the observed data (in the Avg. column), and median values of the observed data (in the Med. column) in each experiment for decision variables $t$ and $q$. The table also indicates the p-values of the Wilcoxon Signed-Rank tests that we used to measure the statistical significance of the deviations (Wilcoxon, 1945). We tested the null hypothesis that the median difference between the predicted equilibrium value and the observed data of the operational decision is equal to zero. We observe that for most experiments, the median difference is statistically significant. Moreover, the table shows the p-values of the two-dimensional Kolmogrov-Smirnov test that we used to test the null hypothesis that the observed values and predicted equilibrium values of the operational decisions in each experiment come from the same distribution. For most of the experiments, the results reject the null hypothesis.

In general, manufacturers set longer delivery lead times than the model's prediction. Risk and loss aversion might be reasons for this behavior. In the model setting, the cost of operating a direct channel with a low delivery lead time is deterministic, whereas, the benefit from operating that channel is uncertain. This is because the manufacturer's benefit depends on the retailer's stocking quantity decision and realized total demand. Knowing such biases might benefit the players of the game: for example, if the retailer knows this bias of the manufacturer, he should set higher stocking quantity to meet the increased consumer demand in the retailer channel.

In general, retailers set lower stock levels than the model's prediction when the predicted level is high, and higher stock levels than the model's prediction when the predicted level is zero. The behavior of retailers' setting stock levels too low when they should be high and too high when they should be low looks similar to "pull to center effect" (Bostian et al. 2008). In the experiments where *ER* is the manufacturer's optimal dual channel strategy (experiments 1c, 2c, 3c, 7a and 7b), under-stocking was not possible, because the theoretical prediction is zero units. If we ignore these cases, we observe that the retailers set stock levels lower than predicted. The behavior of retailers' setting stock levels too low when they should be high might be caused by risk aversion. In the model setting, the cost of stocking $q$ units is deterministic, whereas, its benefit is uncertain. This is because the retailer's benefit depends also on the manufacturer's delivery lead time decision and realized total demand. If the retailer is risk averse, knowing that fact, the manufacturer should set lower delivery lead time than the analytical model's prediction to avoid a lost demand situation caused by the shortage in the retailer channel.

Table 4.5. Comparing the Equilibrium Predictions with the Observed Data

| Exp. | **Delivery Lead Time $t$** | | | **Stock Level $q$** | | | **p-values** | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | **WRS test** | | **KS test** |
| | Eql. | Avg. | Med. | Eql. | Avg. | Med. | $t$ | $q$ | $(t, q)$ |
| 1a | 13.95 | 16.35 | 15.00 | 495.44 | 364.79 | 350.00 | **0.00** | **0.00** | 1.00 |
| 1b | 23.55 | 25.44 | 25.00 | 258.29 | 253.10 | 300.00 | 0.07 | 0.85 | **0.00** |
| 1c | 10.00 | 10.82 | 10.00 | 0.00 | 45.42 | 0.00 | 0.46 | **0.00** | **0.00** |
| 2a | 13.95 | 18.36 | 15.00 | 495.44 | 393.97 | 400.00 | **0.00** | **0.00** | 1.00 |
| 2b | 23.55 | 29.83 | 25.00 | 258.29 | 238.01 | 300.00 | **0.00** | 0.80 | **0.00** |
| 2c | 10.00 | 9.79 | 10.00 | 0.00 | 21.26 | 0.00 | **0.00** | **0.00** | **0.00** |
| 3a | 15.67 | 17.49 | 15.00 | 593.40 | 476.46 | 500.00 | 0.17 | **0.00** | **0.00** |
| 3b | 34.32 | 46.49 | 30.00 | 337.83 | 355.76 | 400.00 | 0.75 | **0.00** | **0.00** |
| 3c | 4.00 | 11.91 | 8.00 | 0.00 | 108.18 | 0.00 | **0.00** | **0.00** | 1.00 |
| 4a | 24.56 | 27.42 | 28.00 | 461.12 | 389.85 | 400.00 | **0.04** | **0.00** | 1.00 |
| 4b | 24.56 | 26.71 | 26.00 | 461.12 | 390.00 | 381.00 | **0.02** | **0.00** | 1.00 |
| 5a | 24.56 | 29.80 | 29.00 | 461.12 | 353.59 | 350.00 | **0.00** | **0.00** | **0.00** |
| 5b | 24.56 | 27.25 | 25.00 | 461.12 | 350.44 | 345.00 | **0.00** | **0.00** | **0.00** |
| 6a | 18.34 | 18.47 | 17.00 | 288.91 | 119.41 | 0.00 | 0.87 | **0.00** | **0.00** |
| 6b | 18.34 | 16.77 | 16.00 | 288.91 | 142.85 | 0.00 | **0.00** | **0.00** | **0.00** |
| 7a | 4.00 | 7.67 | 10.00 | 0.00 | 0.33 | 0.00 | 0.28 | 0.32 | **0.01** |
| 7b | 4.00 | 5.21 | 4.00 | 0.00 | 2.82 | 0.00 | **0.00** | **0.00** | 1.00 |

These results generalize the observations of Chen et al. (2008). The analysis in this section shows that the analytical model of Chen et al. (2008) can be used to predict the characteristics of the decisions related to a specific dual channel strategy and the changes in the decisions when the manufacturer shifts from one dual channel strategy to another. However, the subjects' decisions have significant deviations from the model's quantitative predictions. Thus, the quantitative predictions of the model should not be used directly at their quantitative values while decision-making in a real business environment.

#### 4.2.2.2. Learning in the Operational Decisions Game

Here, we aim to understand if the subjects learned how to make better decisions over time. We first controlled if there is dispersion in the decisions of the subjects in each experiment. We calculated dispersion by multivariate standard deviation normalized by the mean values. The related formula is:

$$\sqrt{\frac{\sum_{i=1}^{n}((t_i-\bar{t})/\bar{t})^2+\sum_{i=1}^{n}((q_i-\bar{q})/\bar{q})^2}{n-1}}$$

where $(t_i, q_i)$ shows a data point related to a period, n is the number of observations (number of data points), and $\bar{t}$ and $\bar{q}$ are the means of the delivery lead time and stock level decisions, respectively. We divide the deviations by their respective mean values for normalization. This normalized measure prevents the stocking level $(q_i)$ values, which are considerably larger, to dominate the delivery lead time $(t_i)$ values. In Figure 4.2, we compare the dispersion of the decisions in the first half with the dispersion of the decisions in the second half in each experiment.

Operational decisions data exhibits significant dispersion. We expect that the subjects would search better strategies during the experiment. If so, the subjects would learn how to make better decisions over time, in which case the dispersion in their decisions would decrease and mean of their decisions would move towards the Nash equilibrium predicted by the model. However, as shown in Figure 4.2, dispersion increases from the first half to second for most of the experiments.

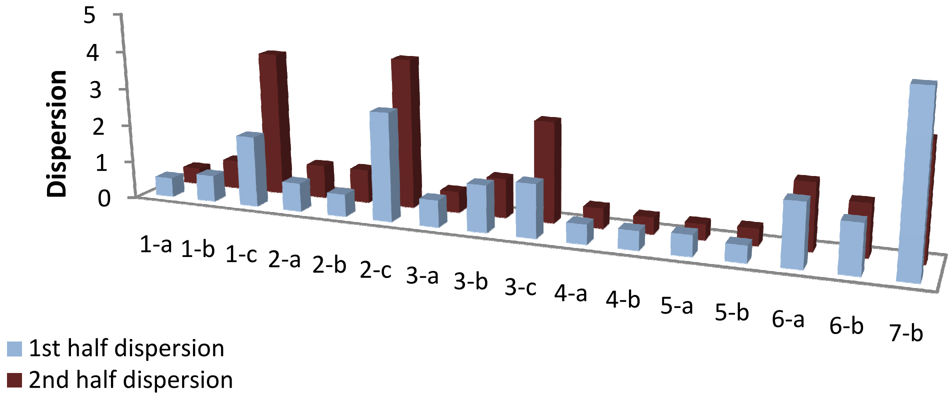



Figure 4.2. Comparison of Dispersion in the Two Halves of the Experiments

Second, we tested the null hypothesis that the decisions from the two halves of the experiment come from the same distribution.

Table 4.6. Comparing the Stage II Decisions in the Two Halves of Each Experiment

| Exp. | Delivery Lead Time $t$ | | | Stock Level $q$ | | | p-values | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | KS test | | | WRS test | |
| | Eql. | 1st Half Avg. | 2nd Half Avg. | Eql. | 1st Half Avg. | 2nd Half Avg. | $t$ | $q$ | $(t, q)$ | $t$ | $q$ |
| 1a | 13.95 | 17.31 | 15.38 | 495.44 | 391.83 | 337.39 | 0.33 | **0.00** | **0.00** | 0.08 | **0.00** |
| 1b | 23.55 | 26.39 | 24.50 | 258.29 | 277.21 | 229.00 | 0.53 | 0.13 | 0.13 | 0.47 | 0.27 |
| 1c | 10.00 | 10.75 | 10.89 | 0.00 | 71.70 | 18.73 | **0.02** | 0.14 | **0.00** | 0.15 | **0.01** |
| 2a | 13.95 | 18.57 | 18.15 | 495.44 | 398.64 | 389.24 | **0.03** | 0.72 | 0.07 | **0.00** | 0.70 |
| 2b | 23.55 | 25.77 | 33.95 | 258.29 | 240.39 | 235.59 | **0.01** | **0.04** | **0.00** | **0.01** | 0.18 |
| 2c | 10.00 | 10.25 | 9.32 | 0.00 | 39.90 | 2.32 | 0.95 | 0.70 | 0.56 | 0.72 | 0.26 |
| 3a | 15.67 | 16.38 | 18.63 | 593.40 | 459.70 | 493.57 | 0.33 | 0.97 | 0.49 | 0.12 | 0.71 |
| 3b | 34.32 | 44.77 | 48.21 | 337.83 | 376.43 | 335.09 | 0.23 | 0.91 | 0.29 | 0.19 | 0.47 |
| 3c | 4.00 | 16.32 | 7.50 | 0.00 | 164.80 | 51.56 | **0.00** | **0.02** | **0.00** | **0.00** | **0.01** |
| 4a | 24.56 | 26.87 | 27.98 | 461.12 | 388.74 | 390.98 | 0.59 | 0.59 | 0.38 | 0.42 | 0.57 |
| 4b | 24.56 | 26.50 | 26.93 | 461.12 | 378.04 | 401.97 | 0.83 | 0.12 | 0.23 | 0.56 | 0.07 |
| 5a | 24.56 | 30.80 | 28.80 | 461.12 | 365.98 | 341.20 | 1.00 | 0.28 | 0.45 | 0.74 | 0.16 |
| 5b | 24.56 | 26.98 | 27.51 | 461.12 | 372.95 | 327.93 | 0.91 | 0.16 | 0.18 | 0.73 | **0.04** |
| 6a | 18.34 | 19.44 | 17.38 | 288.91 | 116.67 | 122.50 | 1.00 | 1.00 | 0.51 | 0.33 | 0.91 |
| 6b | 18.34 | 16.53 | 17.02 | 288.91 | 138.55 | 147.21 | 1.00 | 0.91 | 0.96 | 0.72 | 0.89 |
| 7a | 4.00 | 10.00 | 3.00 | 0.00 | 0.00 | 1.00 | N/A | N/A | N/A | 0.16 | 0.16 |
| 7b | 4.00 | 6.20 | 4.22 | 0.00 | 4.45 | 1.16 | **0.04** | 1.00 | 0.19 | **0.00** | 0.65 |

In Table 4.6, we provided related p-values for stage II decision variables in each experiment. For one-dimensional test, we tested the null hypothesis for each decision variable $t$ and $q$ separately, whereas, for the two-dimensional test, we tested the $(t, q)$ decisions as a couple. For most of the experiments, we cannot reject the null hypothesis by Kolmogrov-Smirnov (KS) and Wilcoxon Rank-Sum (WRS) tests. As shown in the table, the average decisions (column "Avg.") in the two halves do not indicate a consistent move towards the equilibrium values (column "Eql.").

Third, we analyzed if the decisions in each experiment converge to the predicted equilibrium value or not. We measured the distances of decisions in the two halves of each experiment to the theoretical Nash equilibrium in order to analyze if there is a significant move towards the predicted equilibrium value. We define a "distance" as the absolute value of the difference between a decision point and the equilibrium value.

Table 4.7. Comparing the Distances of Stage II Decisions in the Two Halves of Each Experiment

| **Exp.** | **Distance of Delivery Lead Time $t$** | | | **Distance of Stock Level $q$** | | | **p-values** | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Eql. | 1st Half Avg. | 2nd Half Avg. | Eql. | 1st Half Avg. | 2nd Half Avg. | **KS test** | | **WRS test** | |
| | | | | | | | $t$ | $q$ | $t$ | $q$ |
| 1a | 13.95 | 4.80 | 3.37 | 495.44 | 132.47 | 168.74 | 0.67 | **0.00** | 0.23 | **0.00** |
| 1b | 23.55 | 7.47 | 3.65 | 258.29 | 123.52 | 139.88 | **0.01** | 0.40 | **0.00** | 0.24 |
| 1c | 10.00 | 3.79 | 2.69 | 0.00 | 71.70 | 25.15 | **0.01** | **0.00** | 0.08 | **0.00** |
| 2a | 13.95 | 5.74 | 6.42 | 495.44 | 139.23 | 122.05 | 0.07 | 0.74 | 0.15 | 0.80 |
| 2b | 23.55 | 5.09 | 12.10 | 258.29 | 94.64 | 154.16 | **0.01** | **0.00** | **0.01** | **0.00** |
| 2c | 10.00 | 2.41 | 0.68 | 0.00 | 39.90 | 2.32 | 0.44 | 0.70 | **0.03** | 0.26 |
| 3a | 15.67 | 6.98 | 7.09 | 593.40 | 167.40 | 152.44 | 0.73 | 0.92 | 0.81 | 0.47 |
| 3b | 34.32 | 27.92 | 26.51 | 337.83 | 120.17 | 135.28 | 0.62 | 0.47 | 0.78 | 0.36 |
| 3c | 4.00 | 12.32 | 3.66 | 0.00 | 164.80 | 51.56 | **0.00** | **0.02** | **0.00** | **0.01** |
| 4a | 24.56 | 7.62 | 9.09 | 461.12 | 109.40 | 128.02 | 0.29 | 0.31 | 0.09 | 0.09 |
| 4b | 24.56 | 6.90 | 7.07 | 461.12 | 126.30 | 108.57 | 0.49 | 0.12 | 0.55 | 0.08 |
| 5a | 24.56 | 9.34 | 7.22 | 461.12 | 117.96 | 129.51 | 0.97 | 0.56 | 0.71 | 0.31 |
| 5b | 24.56 | 4.81 | 4.56 | 461.12 | 133.03 | 160.43 | 0.91 | 0.16 | 0.44 | 0.06 |
| 6a | 18.34 | 2.59 | 2.21 | 288.91 | 232.73 | 266.96 | 1.00 | 0.99 | 0.72 | 0.55 |
| 6b | 18.34 | 2.97 | 3.16 | 288.91 | 200.15 | 214.21 | 1.00 | 0.94 | 0.76 | 0.62 |
| 7a | 4.00 | 6.00 | 1.00 | 0.00 | 0.00 | 1.00 | N/A | N/A | 0.16 | 0.16 |
| 7b | 4.00 | 2.20 | 0.24 | 0.00 | 4.45 | 1.16 | **0.04** | 1.00 | **0.00** | 0.65 |

We tested the null hypothesis that the distances of the decisions in the first half and the second half of an experiment are drawn from the same population. As indicated by the p-values in Table 4.7, for most of the experiments, we cannot reject the null hypothesis by one-dimensional Kolmogrov-Smirnov (KS) and Wilcoxon Rank-Sum (WRS) tests. The average distances in the two halves do not indicate a consistent improvement. Thus, we cannot say that the decisions move towards the equilibrium value, in general.

There are some experiments that have significant differences between the two halves. For these, we can talk about an improvement in the direction of the predicted equilibrium or vice versa. The comparison of the average values and the standard deviations of the distances in the two halves may provide an intuition for the direction of the move. For instance, we observe that the delivery lead times in experiment 1b, 3c and 7b, and the stock levels in experiment 1c and 3c are improved from the first half to the second in the direction of predicted equilibrium value. In

Figure 4.3, we provide the histogram plots of distances of delivery lead time decisions to equilibrium in experiment 7b. As seen from the histogram plots, distances in the second half are relatively smaller than the distances in the first half. We conclude that if the distances in the first and second halves of an experiment do not come from the same distribution, one reason for that might be learning in the direction of the predicted equilibrium.

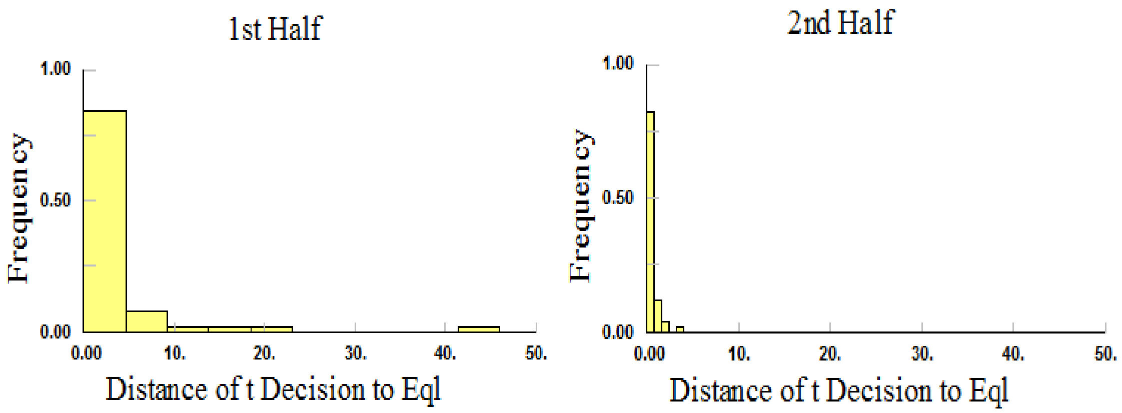



Figure 4.3. Histogram of Distances of Delivery Lead Time Decisions to Equilibrium in Experiment 7b

To sum up, we could not found strong evidence for the existence of learning in our experiments.

#### 4.2.2.3. Effect of Experiment Type on Operational Decisions

Here, we analyze whether the experiment type affects operational decisions or not. To do this, we compare the subjects' behavior in the given-w and w-setting experiments within sessions 4, 5, 6 and 7. Figure 4.4 provides the comparison for session 5, which suggests that the operational decisions data of the two experiments do not come from different distributions.

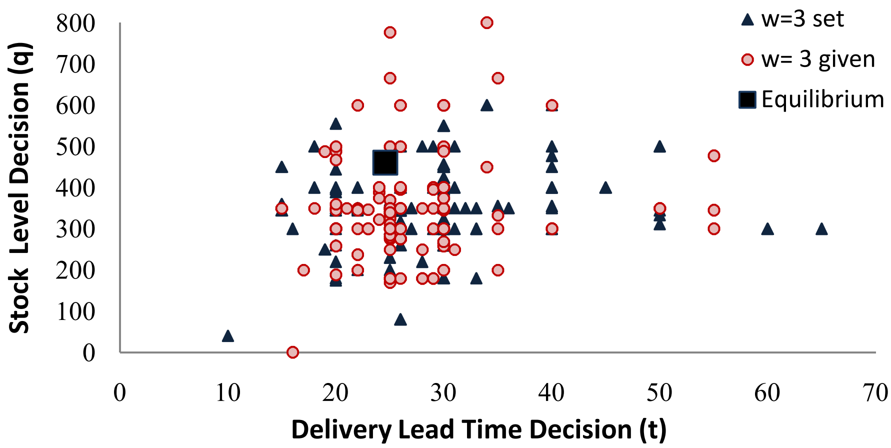



Figure 4.4. Comparing Given versus Set Wholesale Price Experiments for Session 5

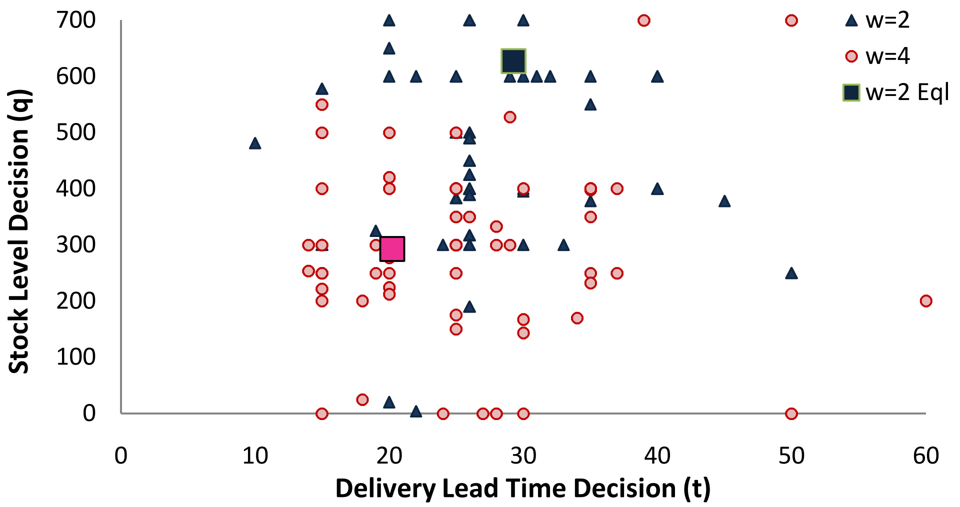
From Table 4.8, we observe that the average decisions in given-w experiments and w-setting experiments are quite close to each other. We tested the null hypothesis that the $t$ decisions in the given-w and w-setting experiments in a session have identical distribution function and the null hypothesis that the $q$ decisions in the given-w and w-setting experiments in a session have identical distribution function. As the p-values of the Wilcoxon Rank-Sum test illustrate, the only significant difference is in the t decisions of session 6. Hence, we conclude that whether the optimal wholesale price is exogenously given or set by the manufacturer does not make a significant difference in stage II decisions.

Table 4.8. Comparison of the Decisions in w-Setting and Given-w Experiments in Sessions 4-7

| Session | Average $t$ | | p-value | Average $q$ | | p-value |
|---|---|---|---|---|---|---|
| | Given $w$ | Set $w$ | | Given $w$ | Set $w$ | |
| **4** | 26.71 | 27.42 | 0.55 | 390.00 | 389.85 | 0.94 |
| **5** | 27.25 | 29.80 | 0.07 | 350.44 | 353.59 | 0.21 |
| **6** | 16.77 | 18.47 | **0.03** | 142.85 | 119.41 | 0.61 |
| **7** | 5.21 | 7.67 | 0.30 | 2.82 | 0.33 | 0.44 |

#### 4.2.2.4. Effect of Wholesale Price on Operational Decisions

Here, we compare the w-setting experiment stage II results for different wholesale values that the manufacturer set in a given experiment. Figure 4.5 and Figure 4.6 compare the results by the wholesale price for experiments 4a and 5a, respectively. As seen from figures, when wholesale price increases in a given experiment, the subjects set shorter delivery lead times and lower stocking quantities in the stage II game. This observation is consistent with the analytical model's qualitative predictions. The dispersion and deviation characteristics of data can also be observed from the figures.



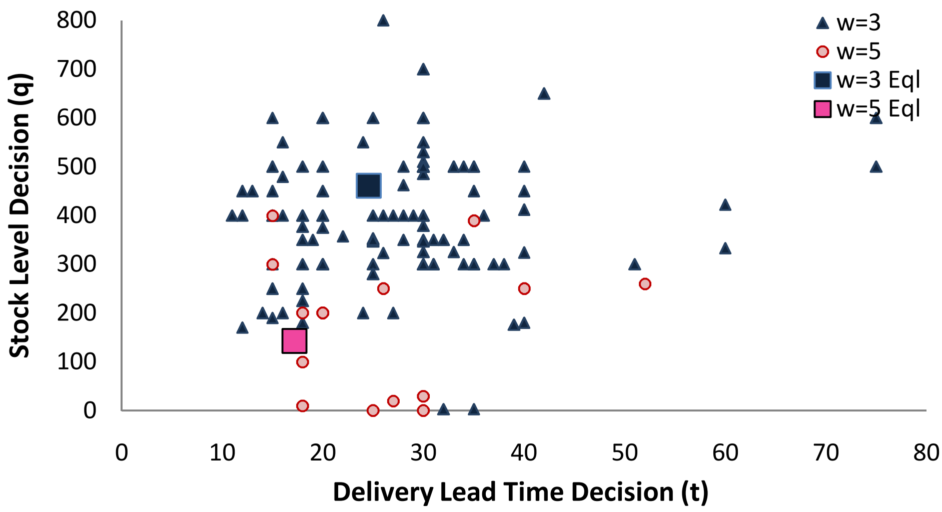



Figure 4.5. Decisions by the Wholesale Prices in Experiment 4a

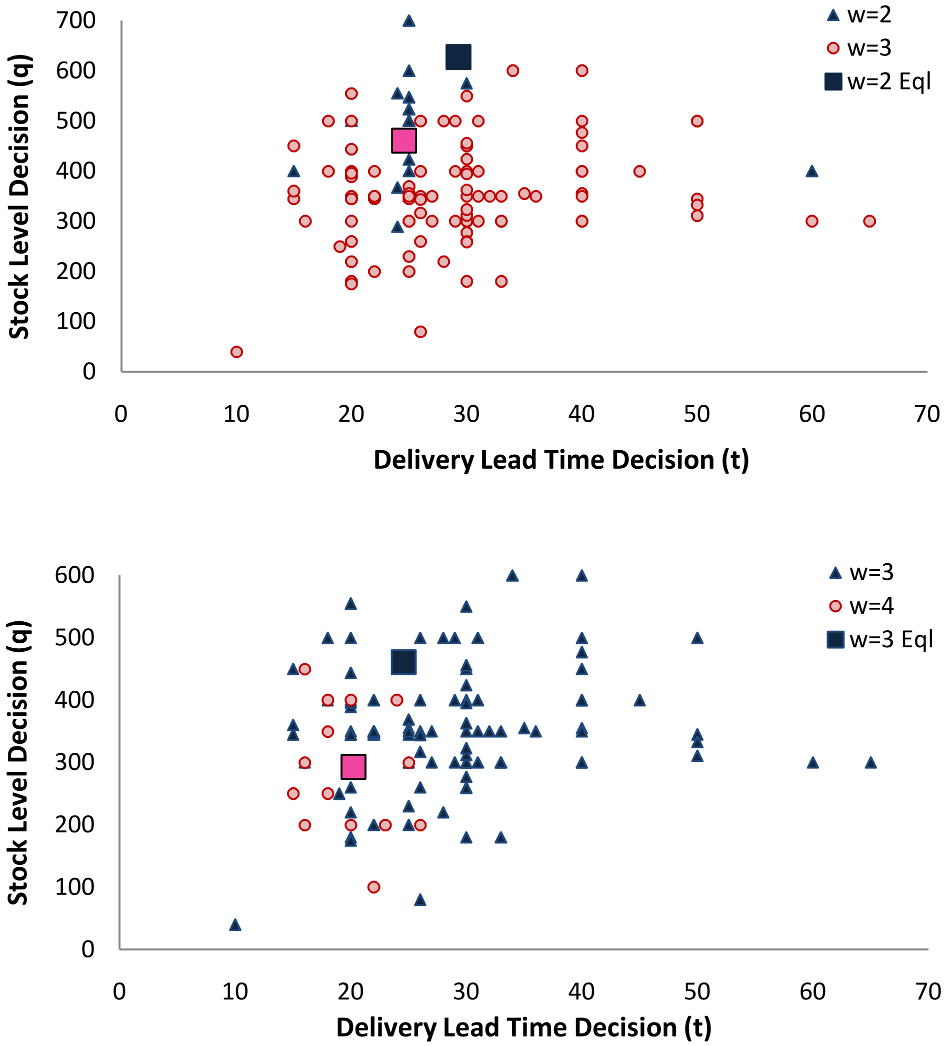



Figure 4.6. Decisions by the Wholesale Prices in Experiment 5a

In order to compare the stage II results by the wholesale price statistically, we conducted two-dimensional Kolmogrov-Smirnov tests. We tested the null hypothesis that the $(t, q)$ decisions by the wholesale prices in a given experiment are drawn from the same population. Table 4.9, Table 4.10, Table 4.11 and Table 4.12 show the test results related to the wholesale price pairs in experiments 4a, 5a, 6a and 7a, respectively.

Table 4.9. Comparison of the Stage II Decisions by the Wholesale Price in Experiment 4a

| **Exp 4a** | **w=2** | **w= 3** | **w=4** |
|---|---|---|---|
| **w=2** | N/A | 0.0553 | **0.0031** |
| **w=3** | 0.0553 | N/A | **0.0018** |
| **w=4** | **0.0031** | **0.0018** | N/A |

Table 4.10. Comparison of the Stage II Decisions by the Wholesale Price in Experiment 5a

| **Exp 5a** | **w=2** | **w= 3** | **w=4** |
|---|---|---|---|
| **w=2** | N/A | **0.0000** | **0.0003** |
| **w=3** | **0.0000** | N/A | **0.0001** |
| **w=4** | **0.0003** | **0.0001** | N/A |

Table 4.11. Comparison of the Stage II Decisions by the Wholesale Price in Experiment 6a

| **Exp 6a** | **w=2** | **w=3** | **w=4** | **w=5** |
|---|---|---|---|---|
| **w=2** | N/A | **0.0063** | **0.0000** | **0.0000** |
| **w=3** | **0.0063** | N/A | **0.0001** | **0.0000** |
| **w=4** | **0.0000** | **0.0001** | N/A | 0.9511 |
| **w=5** | **0.0000** | **0.0000** | 0.9511 | N/A |

Table 4.12. Comparison of the Stage II Decisions by the Wholesale Price in Experiment 7a

| Exp 7a | w=2 | w= 3 | w=4 | w=5 |
|---|---|---|---|---|
| **w=2** | N/A | 0.0705 | **0.0489** | **0.0032** |
| **w=3** | 0.0705 | N/A | **0.0000** | **0.0000** |
| **w=4** | **0.0489** | **0.0000** | N/A | **0.0000** |
| **w=5** | **0.0032** | **0.0000** | **0.0000** | N/A |

Most of the results support our observations from the figures above, and we reject the null hypothesis that the $(t, q)$ decisions by the wholesale prices in a given experiment come from the same distribution. We have strong evidence that subjects react at stage II to the wholesale price set at stage I.

### 4.2.3. Results in Stage I Decision

We analyze stage I decisions in two parts. First, we check if the manufacturer subjects chose the theoretically optimal wholesale price or not. Second, we control if there is any learning in the wholesale price decisions or not.

#### 4.2.3.1. Comparing the Theoretical Optimum Predictions and Observed Data

Theory assumes that the manufacturer subjects can "foresee" the outcome of the stage II game, and set the stage I decision (i.e., the wholesale price $w$) accordingly. Hence, we are interested in comparing their decisions with the theoretical predictions.

Figure 4.7 presents the wholesale price choices of subjects in w-setting experiments. The figure illustrates the number of times that a specific wholesale price is selected in each experiment. Theoretical optimal $w$ of each experiment are marked with an asterix. In general, we observe that the manufacturer subjects choose the theoretically optimal value or one value below the theoretical optimal, most frequently.

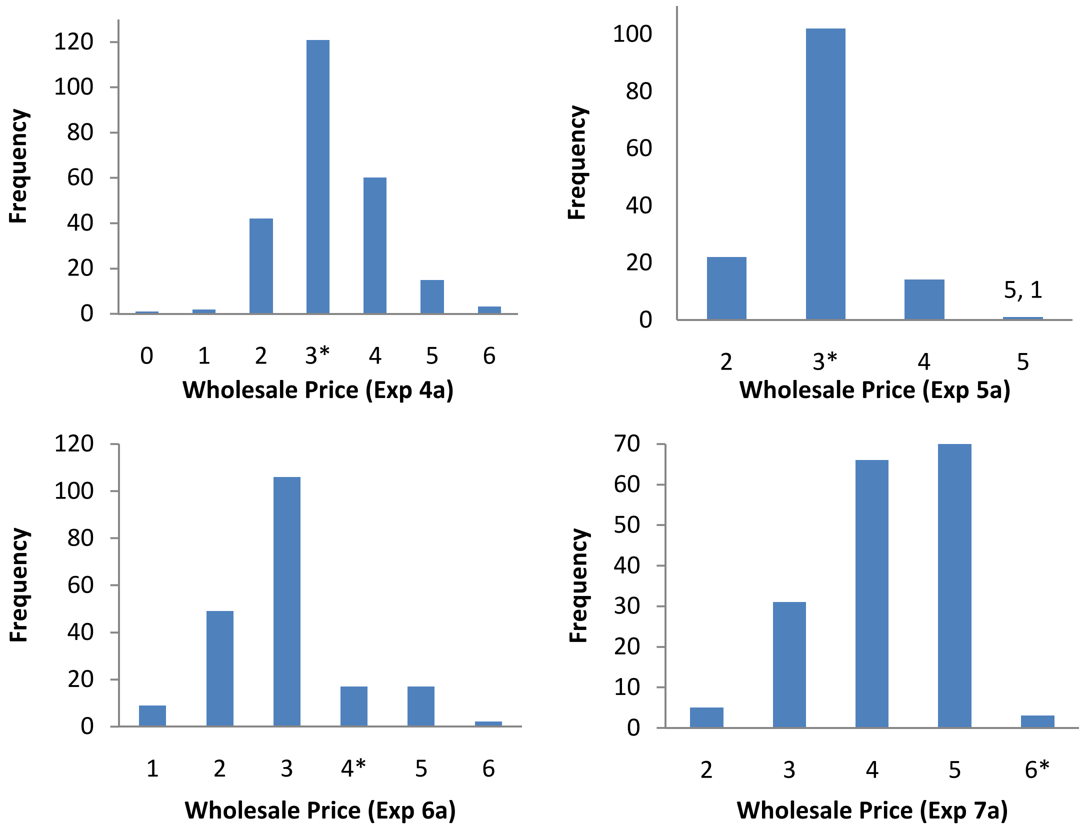



Figure 4.7. Comparison of Wholesale Price Choice in w-setting Experiments

The "theoretical optimal" wholesale price assumes that the players will play the Nash equilibrium at stage II. However, we know that their choices deviate significantly from the equilibrium predictions. Hence, the theoretical optimum wholesale price may not be the practical optimum to set at stage I. Thus, the reason for why the subjects did not select optimal $w$ in some of the w-setting experiments most frequently might be that the most selected $w$ is more profitable than the theoretical optimum. Table 4.13 compares the manufacturer's average realized profit with the theoretical optimal $w$, with the practical optimal $w$ (i.e., the observed optimal $w$ that resulted in the highest observed manufacturer's profit) and with the most frequently selected $w$.

Table 4.13. Manufacturer's Profit Comparison for w-setting Experiments

| Exp. | Theoretical Optimal $w$ | | Practical Optimal $w$ | | Most Selected $w$ | |
|---|---|---|---|---|---|---|
| | $w$ | Manufacturer's Average Profit | $w$ | Manufacturer's Average Profit | $w$ | Manufacturer's Average Profit |
| 4a | 3 | 1317.99 | 4 | 1416.30 | 3 | 1317.99 |
| 5a | 3 | 1239.00 | 5 | 2846.00 | 3 | 1239.00 |
| 6a | 4 | 1115.88 | 3 | 1531.58 | 3 | 1531.58 |
| 7a | 6 | 1263.00 | 5 | 2161.16 | 5 | 2161.16 |

We observe that the subjects selected theoretical optimal $w$ most frequently only in experiments 4a and 5a. However, the optimal $w$ did not turn out to be the most profitable. For experiments 6a and 7a, the subjects did not select the theoretical optimal $w$, but they selected the most profitable one. That is, they were successful in anticipating the stage II outcome, although this outcome is different from what is predicted by theory.

#### 4.2.3.2. Learning in the Wholesale Price Decision

In section 4.2.2.2., we could not find significant learning effect in stage II decisions. Here, we aim to find if the manufacturer subjects learned how to make better wholesale price decisions over time in the w-setting experiments.

First, we compare the wholesale price decisions in the first and the second halves of each experiment by conducting Wilcoxon Rank-Sum and Kolmogrov-Smirnov tests. We tested the null hypothesis that the wholesale price decisions in the two halves of an experiment have identical distribution function. Table 4.14 shows mean values ("Avg.") of the wholesale price decisions in the first and second halves of each experiment, theoretical optimal wholesale price ("Opt. w") in each experiment and p-values ("p-value") related to each test. For all experiments except 6a, we cannot reject the null hypothesis that wholesale price decisions in the first and the second halves of an experiment come from the same distribution. In addition, as shown in the table, mean values do not change from first half to second half consistently.

Table 4.14. Comparing the Wholesale Price Decisions in the Two Halves of Each Experiment

| | | | | WRS test | KS test |
|---|---|---|---|---|---|
| **Exp.** | **Opt. w** | **Avg. *w* of 1st Half** | **Avg. *w* of 2nd Half** | **p-value** | **p-value** |
| 4a | 3 | 3.30 | 3.11 | 0.14 | 0.40 |
| 5a | 3 | 3.00 | 2.91 | 0.40 | 1.00 |
| 6a | 4 | 3.13 | 2.77 | **0.02** | **0.00** |
| 7a | 6 | 4.14 | 4.26 | 0.30 | 0.45 |

Hence the only experiment that shows signs of learning is experiment 6a. Figure 4.8 shows that the average wholesale price in experiment 6a decrease over periods. Note however that the average wholesale price is not moving towards the theoretical optimal value 4, but to practical optimal value 3.

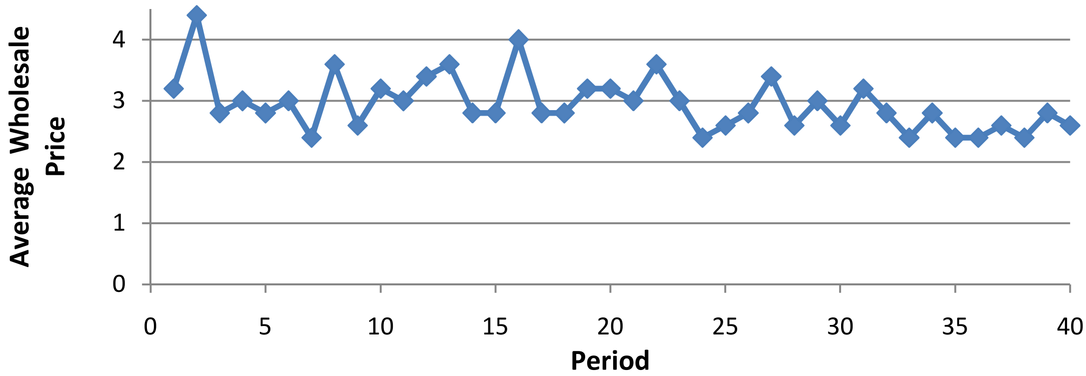



Figure 4.8. Average Wholesale Price per Period in Session 6

Given this observation, we analyze if the wholesale price decisions converge to the theoretical optimal value or not, for all four experiments. To this end, we measured the distances of wholesale price decisions to the theoretical optimal value in the first half and the second half of each experiment. We tested the null hypothesis that the distances of the wholesale price decisions to the theoretical optimal value in the two halves of an experiment are drawn from the same population. As shown in Table 4.15, the only significant difference between the distances appears in experiment 4a with the Wilcoxon Rank-Sum test. The Kolmogrov-Smirnov test detects no significant difference. In addition, the average distances (presented under column "Avg.") and the standard deviation of distances (presented under column "StDev.") in the two halves do not indicate a consistent improvement. Thus, we cannot say that the decisions move towards the theoretical optimal, in general.

Table 4.15. Comparing the Distances of Wholesale Price Decisions in the Two Halves of Each Experiment

| | | **Distance of *w* in the 1st Half** | | **Distance of *w* in the 2nd Half** | | **KS test** | **WRS test** |
|---|---|---|---|---|---|---|---|
| **Exp.** | **Opt. w** | Avg. | StDev. | Avg. | StDev. | p-value | p-value |
| 4a | 3 | 0.70 | 0.71 | 0.52 | 0.66 | 0.32 | **0.04** |
| 5a | 3 | 0.29 | 0.49 | 0.26 | 0.44 | 1.00 | 0.85 |
| 6a | 4 | 1.23 | 0.79 | 1.29 | 0.54 | 0.58 | 0.30 |
| 7a | 6 | 1.87 | 0.90 | 1.74 | 0.80 | 0.38 | 0.26 |

# CHAPTER 5

## CHAPTER 5 : EXPERIMENTAL STUDY OF BUYBACK CONTRACT MODEL

In this chapter, we explain and analyze the experimental study that we conducted on our buyback contract model. First, we give information on the experimental procedure and design. Then we focus on the analysis of the experimental data.

### 5.1. Experimental Procedure and Design

Our experiments are computer-based and were conducted at the CAFE (Center for Applied Finance Education) computer laboratory of Sabancı University. We coded and implemented the buyback contract version of the experimental model with HP MUMS software. As an example for the experiment code, in Appendix D, we provide the main script code that is used to define the number of subjects, and to call other functional scripts. Appendix E illustrates another important part of the code where the parameters $(v, p, k, m, a)$, and contract parameters $(w, b)$, the stages and the allocation strategy of subjects to the roles are defined.

Subjects are selected from Sabancı University MS 454 course Fall 2010/2011 students. We distributed instructions to the subjects before they came to the experiments to reduce the training time during the experimental session. Sample instructions are provided in Appendix F. At the beginning of each session, we made a short quiz on the instructions to make sure that the subjects understood the mechanism of the experiment, and eliminated the subjects who failed to pass the quiz. After the quiz, we let the subjects play several pilot (training) periods. Before beginning to each session, an experimenter explained the details of the game and answered the questions of the subjects. During the experiments, we did not let the subjects communicate with each other.

To provide incentive, the subjects' total profit at the end of the experimental session is converted into a bonus grade for the course MS 454. The maximum bonus was set as 1.5% applied to the final grade of the subject in that course. A survey on the experiments is conducted to the students after each session. In this survey, their suggestions and general opinion related to the experiments is asked.

We conducted 7 experiments in 6 sessions. Only session 6 had two experiments (played by the same group of subjects). Each session lasted around 2.5 hours. In each experiment, the same game is played for 30 independent periods. General view of the experimental design is provided in Table 5.1.

Table 5.1. General View of the Experimental Design

| **Session** | **# Subjects** | **Exp.** | **# Periods** | **Experiment Type** |
|---|---|---|---|---|
| 1 | 10 | b1a | 30 | w & b setting |
| 2 | 8 | b2a | 30 | w & b setting |
| 3 | 14 | b3a | 30 | given-w as 3 |
| 4 | 12 | b4a | 30 | w & b setting |
| 5 | 8 | b5a | 30 | w & b setting |
| 6 | 12 | b6a | 30 | given-w as 5 |
| 6 | 12 | b6b | 19 | given-w as 5 and given-b as 3 |

Each subject was randomly matched with another subject at the beginning of each period. Subjects did not know with whom they were matched. A subject from each pair was randomly selected as manufacturer and the other as the retailer. Participating in both roles helped the subjects to understand the whole game, which is consistent with the full information assumption of the analytical model. Moreover, a specific subject played the role of the manufacturer and the retailer in equal number of times, which led to a fair distribution of monetary rewards. This is because the expected payoff of the manufacturer and the retailer are not equal in an experiment. The code, which is used to match the subjects and assign them to the manufacturer and the retailer roles, can be seen in Appendix E. At the end of each session, the subjects' cumulative payoff is reported.

In the most general type of experiments, there are three stages. At stage I, the manufacturer sets the wholesale price (as an integer between 0 and the sales price $p$), and the buyback price (as an integer between 0 and the wholesale price)[6]. At stage II, given the wholesale and buyback prices, the manufacturer decides on the delivery lead time, and the retailer decides on the stock level simultaneously. At stage III, a random number of consumers are generated by the software, and the demand in each channel and the profit of each firm are realized. If both of the contract parameters are exogenously given, the experiment started directly from stage II. At each stage, 45 seconds is given to the subjects to make decisions.

We provided a decision support tool in subjects' screens during the experiments. By using this tool, the subjects could run what-if analysis before entering their decisions. For instance, the retailer subject can enter a stocking level and his guess on the manufacturer subject's delivery lead time to this tool and achieve the results for 11 different realizations of the random total market demand ($X = 0, 100, 200 \ldots 1000$). More detailed explanation about the decision support tool can be found in Appendix F. Subjects enter their decisions into the boxes at the bottom of the screens. At the end of each period, each subject learned the total demand realization, operational decision of his counterpart, number of units sold in each channel, number of lost customers, and his profit in the period. In addition, a historical results page was provided to every subject, presenting all previous periods' results for that subject.

There are three types of buyback contract experiments depending on the contract parameters $(w, b)$ being set by the manufacturer or exogenously given:

- w & b setting: This type of experiments start from stage I where the manufacturer sets contract parameters $(w, b)$.
- given-w & b-setting: This type of experiments starts from stage I where the manufacturer sets contract parameter $(b)$ at stage I. Wholesale price $(w)$ is exogenously given.
- given w & b: This type of experiments start from stage II, and contract parameters $(w, b)$ are assumed to be exogenously given. Stage I is skipped.

Table 5.2 shows the experimental design for w & b setting experiments.

[6] We constrained the wholesale price and buyback price decisions to integer values to facilitate the decision-making process of subjects and our analysis. As the unit production cost is assumed to be 0, the lowest wholesale price to set is equal to 0.

Table 5.2. Experimental Design for w & b Setting Experiments

| Session | # Subjects | Exp. | # Periods | $k$ | $m$ | $v$ | $p$ |
|---|---|---|---|---|---|---|---|
| 1 | 10 | b1a | 30 | 2 | 100,000 | 10 | 6 |
| 2 | 8 | b2a | 30 | 2 | 100,000 | 10 | 6 |
| 4 | 12 | b4a | 30 | 8 | 200,000 | 15 | 6 |
| 5 | 8 | b5a | 30 | 0 | 10,000 | 10 | 6 |

The parameters $(k, m, v, p, c)$ of the experiments are set to match the parameters in the wholesale price contract experiments (WPCE), as compared in Table 5.3. We used the same parameter settings to compare the experimental results of WPCE with BCE, which is discussed in Section 6. Note that the optimum "channel strategy" turns out to be "share profit" with the BCM for all of these parameter settings.

Table 5.3. Parameter Settings Used in Both Contract Type of Experiments

| Experiment | | Theoretical Optimal Dual Channel Strategy | | Theoretical Optimal Stage I Decisions | | Parameters | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| WPCE | BCE | WPCM | BCM | $(w)$ | $(w, b)$ | $k$ | $m$ | $v$ | $p$ | $c$ |
| 4a - 5a | b1a - b2a | *SP* | *SP* | (3) | (5, 5) | 2 | 100,000 | 10 | 6 | 0 |
| 6a | b4a | *CP* | *SP* | (4) | (5, 5) | 8 | 200,000 | 15 | 6 | 0 |
| 7a | b5a | *ER* | *SP* | (6) | (5, 5) | 0 | 10,000 | 10 | 6 | 0 |

Table 5.4 shows the experimental design for given-w & b-setting experiments. In these experiments, at stage I, the wholesale price is exogenously given, and the manufacturer determines the buyback price. These experiments have the same parameter set as experiments b1a and b2a. The wholesale price is given as 3 (a non-optimal wholesale price) in experiment b3a and as 5 (the optimal wholesale price) in experiment b6a.

Table 5.4. Experimental Design for Given-w & b-Setting Experiments

| **Session** | **# Subjects** | **Exp.** | **# Periods** | **Exp. Type** | $\boldsymbol{k}$ | $\boldsymbol{m}$ | $\boldsymbol{v}$ | $\boldsymbol{p}$ |
|---|---|---|---|---|---|---|---|---|
| 3 | 14 | b3a | 30 | given-w as 3 | 2 | 100,000 | 10 | 6 |
| 6 | 12 | b6a | 30 | given-w as 5 | 2 | 100,000 | 10 | 6 |

Table 5.5 shows the experimental design for the only given w & b experiment[7]. This experiment has the same parameter setting $(k, m, v, p, c)$ as experiments b1a, b2a, b3a and b6a. Wholesale and buyback prices are given such that the optimal dual channel strategy of the manufacturer is capture all profit.

Table 5.5. Experimental Design for Given w & b Experiment

| **Session** | **# Subjects** | **Exp.** | **# Periods** | **Exp. Type** | $\boldsymbol{k}$ | $\boldsymbol{m}$ | $\boldsymbol{v}$ | $\boldsymbol{p}$ |
|---|---|---|---|---|---|---|---|---|
| 6 | 12 | b6b | 19 | given-w as 5 and given-b as 3 | 8 | 200,000 | 15 | 6 |

## 5.2. Analysis of the Experimental Data

We present the analysis of our experimental data in three parts. First, we provide a general view of the results after eliminating the outliers. Second, we provide our analysis related to stage II decisions. This part covers comparison of the equilibrium predictions and qualitative predictions with observed data, learning in the operational decisions game, and effect of experiment type and buyback price on the operational decisions. Third, we focus on the decisions at stage I where the manufacturer sets the wholesale and buyback prices. In this part, we compare the theoretical optimum predictions and observed data, and analyze learning in the wholesale price and buyback price decisions. Finally, we analyze general trends on the decisions and the relationships between the decision variables.

[7] Note that this experiment only lasted for 19 periods due to a system breakdown.

### 5.2.1. General View of the Data

First, we eliminated outliers from our data, as presented in Appendix G. In total, we eliminated 12 data from our experiment results. In one period of experiment b1a, the manufacturer subject set a buyback price higher than the wholesale price he set, that is detected as outlier and deleted from the data. The rest of the outliers consist of a very high delivery lead time in comparison to the average delivery lead time set in a given experiment. Results provided in the tables below are calculated after eliminating the outliers from the data. We used a significance level of 0.05 for the statistical analysis in the following sections.

Next, we provide the results on delivery lead time t, stocking level q, manufacturer's profit and retailer's profit in each experiment. For each of these, we show the model's theoretical predictions under column "Eql." and mean of the observed data under column "Avg.". Table structures differ with respect to the experiment type. We provide the results related to w & b setting experiments, given-w & b-setting experiments, and given w & b experiments separately.

**General View of the Results for w & b Setting Experiments**

Table 5.6. General View of the Results for w & b Setting Experiments

| | **Wholesale Price *w*** | | **Buyback Price *b*** | | **Delivery Lead Time *t*** | | **Stock Quantity *q*** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b1a | 5 | 4.5 | 5 | 2.3 | 200 | 26 | 990 | 413 | 2503 | 1619 | 495 | 286 |
| b2a | 5 | 4.4 | 5 | 2.2 | 200 | 24 | 990 | 357 | 2503 | 1417 | 495 | 265 |
| b4a | 5 | 4.6 | 5 | 1.8 | 100 | 29 | 920 | 359 | 2520 | 1699 | 460 | -264 |
| b5a | 5 | 4.7 | 5 | 2.3 | $\infty$ | 9 | 1000 | 436 | 2500 | 2153 | 500 | 243 |

As seen in Table 5.6, both the manufacturers and the retailers have lower average observed profits than equilibrium prediction. Although the manufacturers set wholesale prices close to the equilibrium, they did not set the buyback prices as high as in the theory. Thus, the retailers ordered less than predicted. This caused less profit for both firms.

For all of the experiments in Table 5.6, unit production cost is zero and sales price is 6. The theoretical optimal wholesale and buyback prices are equal to 5 for all experiments. Thus, the manufacturer's optimal strategy is to sell the products at a high wholesale price (close to sales price) and to buy the unsold products by paying back the wholesale price. That is, it is optimal for the manufacturer to take all risk from the retailer by setting $w = b = 5$.

Next, we analyze the general results one step deeper by considering only the data in which the manufacturer subjects set the theoretical optimal wholesale price (i.e., $w$=5 for all four experiments above in the table) at stage I. Comparison of the results in Table 5.6 with the results in Table 5.7 indicates an increase in the average buyback prices and manufacturer's average profit. Average delivery lead time is closer to the Nash equilibrium, but the average stock level and the retailer's average profit deviated from the Nash equilibrium more in comparison to the general results stated in the previous table.

Table 5.7. Observed Results for Theoretical Optimal w in w & b Setting Experiments

| | | | **Buyback Price *b*** | | **Delivery Lead Time *t*** | | **Stock Quantity *q*** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Explanation | # of Data | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b1a | $w$ = 5 data | 76 | 5 | 2.9 | 200 | 26 | 990 | 397 | 2503 | 1809 | 495 | 169 |
| b2a | $w$ = 5 data | 42 | 5 | 2.8 | 200 | 28 | 990 | 302 | 2503 | 1547 | 495 | 166 |
| b4a | $w$ = 5 data | 72 | 5 | 2.4 | 100 | 34 | 920 | 374 | 2520 | 1916 | 460 | -311 |
| b5a | $w$ = 5 data | 76 | 5 | 2.6 | $\infty$ | 7 | 1000 | 404 | 2500 | 2380 | 500 | 128 |

Next, we focus even more and consider only the data for which the manufacturer subjects chose the theoretical optimal $(w, b)$ couple. Table 5.8 presents the results[8]. Note that the number of data points is really low. We observe that, the retailer sets the stock level very close to the equilibrium on average. This profits both the manufacturer and the retailer almost as predicted by the theoretical model.

8 Note that there exist no data for the theoretical optimal $(w, b)$ couple in experiments b2a and b5a.

Table 5.8. Observed Results for Theoretical Optimal (w, b) in w & b Setting Experiments

| | | | **Delivery Lead Time $t$** | | **Stock Quantity $q$** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Explanation | # of Data | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b1a | ($w$=5, $b$=5) data | 6 | 200 | 29 | 990 | 932 | 2503 | 2858 | 495 | 547 |
| b4a | ($w$=5, $b$=5) data | 2 | 100 | 20 | 920 | 850 | 2520 | 2114 | 460 | 291 |

We observe that the results are consistent with the theoretical model's predictions, when the manufacturer chooses the theoretically optimal contract parameters ($w = b = 5$), the retailer orders a high quantity and the manufacturer's profit is quite high. Thus, the model is successful in predicting the stage II outcome if the manufacturer chooses the theoretically optimal contract parameters at stage I. However, we have also shown that the manufacturer usually chooses a lower $w$ and much lower $b$ value than the model's prediction. We will be studying the implications of these choices.

**General View of the Results for Given-w & b-Setting Experiments**

In Table 5.9 we provide the results for given-w and b-setting experiments. When the wholesale price is given as lower than the optimal (i.e., experiment b3a), the retailers' order quantity and profit turns out to be very close to the equilibrium. However, when the wholesale price is given as the optimal, the retailer's profit is relatively less than the equilibrium, because the retailer did not order as much. Behavior of the retailers to order less when the wholesale price is higher is probably due to risk aversion.

Table 5.9. General View of the Results for Given-w & b-Setting Experiments

| | | **Wholesale Price $w$** | | **Buyback Price $b$** | | **Delivery Lead Time $t$** | | **Stock Quantity $q$** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Exp. Type | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b3a | w-given as 3 | 3.0 | 3.0 | 2.0 | 1.7 | 38 | 167 | 716 | 614 | 1713 | 1437 | 1062 | 966 |
| b6a | w-given as 5 | 5.0 | 5.0 | 5.0 | 4.2 | 200 | 48 | 990 | 583 | 2503 | 2002 | 495 | 271 |

Next, we analyze the general results one-step deeper by focusing on the theoretical optimal buyback price data for each given wholesale price. As seen from the results in Table 5.10, in given-w & b-setting experiments, if the manufacturers set optimal buyback price, the average observed results become closer to the equilibrium values. This improvement is similar to what we observed with the w & b setting experiments.

Table 5.10. Observed Results for Theoretical Optimal *b* in Given-w & b-Setting Experiments

| | | | **Delivery Lead Time *t*** | | **Stock Quantity *q*** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Explanation | # of Data | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b3a | w-given as 3 and *b*=2 data | 74 | 38 | 42 | 716 | 619 | 1713 | 1484 | 1062 | 908 |
| b6a | w-given as 5 and *b*=5 data | 91 | 200 | 74 | 990 | 796 | 2503 | 2377 | 495 | 458 |

**General View of the Results for Given w & b Experiments**

The results in Table 5.11 support our finding that if the optimal stage I decisions are given exogenously to the subjects, our theoretical model is more successful in predicting the stage II outcomes.

Table 5.11. General View of the Results for Given w & b Experiments

| | | | **Delivery Lead Time *t*** | | **Stock Quantity *q*** | | **Manufacturer's Profit** | | **Retailer's Profit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | Eql. Type | Exp. Type | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. | Eql. | Avg. |
| b6b | CP | w-given as 5, b-given as 3 | 21 | 27 | 322 | 264 | 2171 | 1624 | 48 | -166 |

In conclusion, the subjects on average set lower wholesale price, buyback price, delivery lead time and stock level in comparison to theoretical predictions. Thus, the manufacturer’s and the retailer’s profit realize lower than predicted.

### 5.2.2. Results in the Stage II Decisions

Here we focus on the operational decisions game at stage II. We aim to determine whether the Nash Equilibrium is a good predictor of the operational decisions game outcome, whether there exists any learning in the operational decisions over time, and whether there is an effect of experiment type or buyback price on the operational decisions at stage II.

#### 5.2.2.1. Comparing the Equilibrium Predictions and Observed Data

We analyze if the Nash equilibrium is a good predictor of the operational decisions game results at stage II. To this end, we focus on stage II decisions of all experiments, independent of whether *w* or *b* was given or set at stage I.

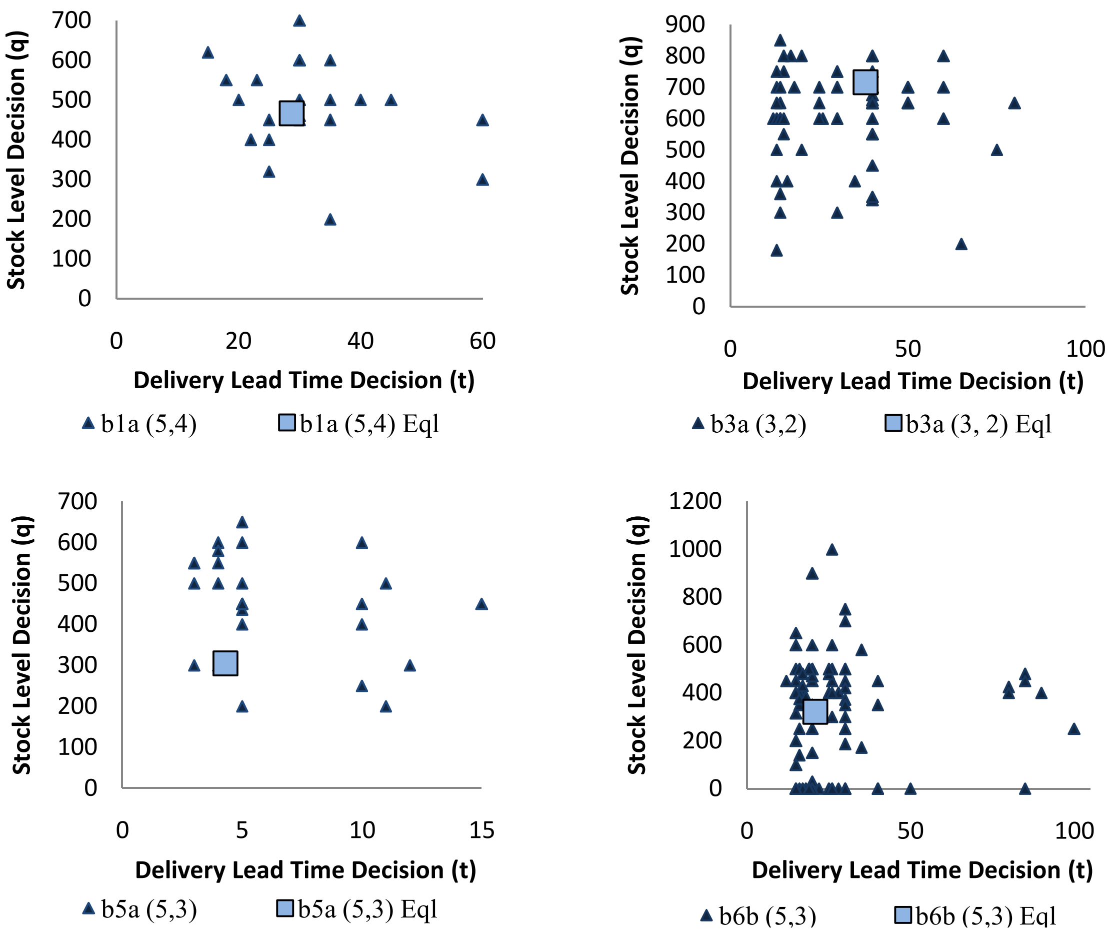



Figure 5.1. Delivery Lead Time and Stock Level Decisions around the Nash Equilibrium

From Figure 5.1, we observe that the delivery lead time and stock level decisions of the subjects (for a given $w$ and $b$) are scattered around the Nash equilibrium. Each triangle in the figure represents the outcome of a one period game between a manufacturer and a retailer, and each square represents the theoretical Nash equilibrium. The given contract parameters ($w$, $b$) are shown in parenthesis. We observe that the model cannot accurately "predict" the quantitative choices of the subjects, and there exists significant dispersion in data. We will study these later.

While the model is not successful in quantitative prediction of the exact decision values, it is successful in predicting how the decisions will change when the parameters change. Figure 5.2 illustrates this result for session 6, in which the same subject set participated in two different experiments. We observe that as predicted by the model, both $q$ and $t$ decisions have increased from experiment b6b ($w$=5, $b$=3 data) to experiment b6a ($w$=5, $b$=5 data). The separation result is supported by a two-dimensional Kolmogrov-Smirnov test with a p-value of less than $10^{-6}$.

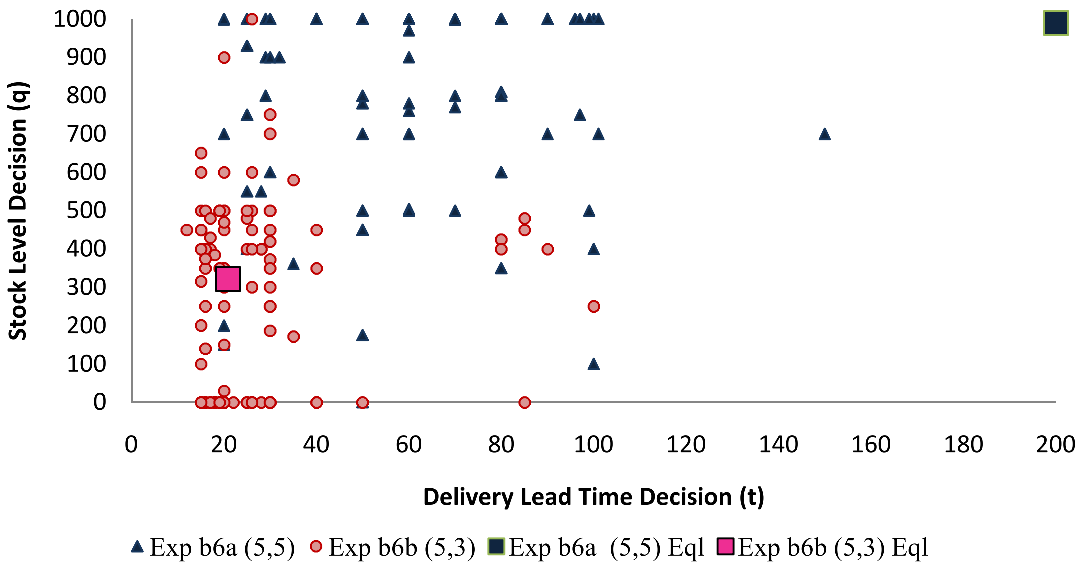


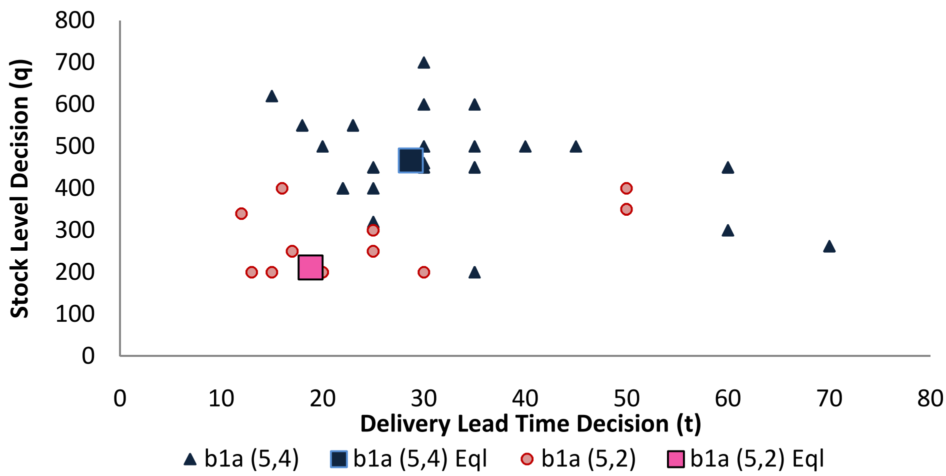

Figure 5.2. Decisions in Experiments b6a ($w$=5, $b$=5 data) and b6b ($w$=5, $b$=3 data)

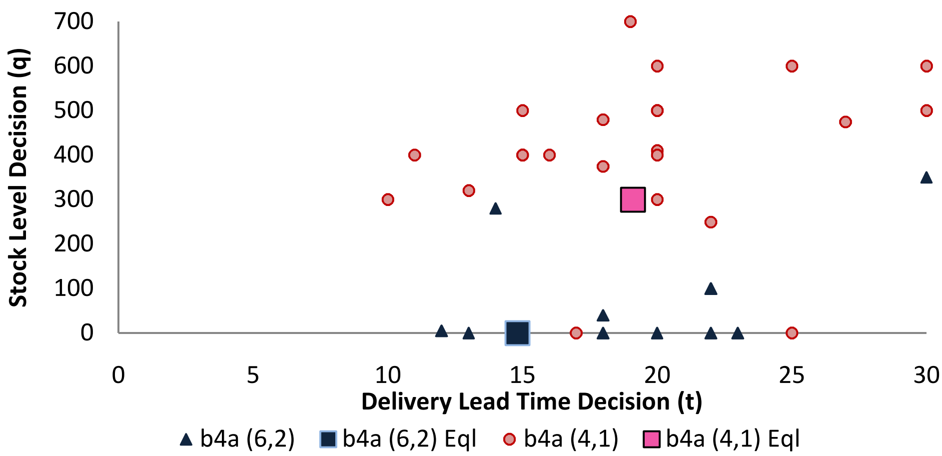
Table 5.12. Average Stage II Decisions in Session 6

| | | | **Delivery Lead Time t** | | **Stock Quantity q** | |
|---|---|---|---|---|---|---|
| Exp. | Eql. Type | ($w$,$b$) | Eql. | Avg. | Eql. | Avg. |
| b6a | SP | 5,5 | 200.00 | 73.70 | 990.00 | 795.79 |
| b6b | CP | 5,3 | 20.80 | 26.59 | 321.80 | 264.39 |

As shown in Table 5.12, the average values of subjects' decisions also reflect the separation.

Session 6 is the only session in which we have one subject set participated in multiple experiments. For other sessions, we analyzed how the subjects' stage II decisions change in a given experiment for different stage I decisions ($w$,$b$). We show the separation results in the stage II decisions in Figure 5.3 for experiments b1a, b4a and b6a. In all of them, the changes are in the predicted directions. We supported the separation results with two-dimensional Kolmogrov-Smirnov tests with p-values less than $10^{-2}$ for experiment b1a, less than $10^{-3}$ for experiment b4a, and less than $10^{-6}$ for experiment b6a.



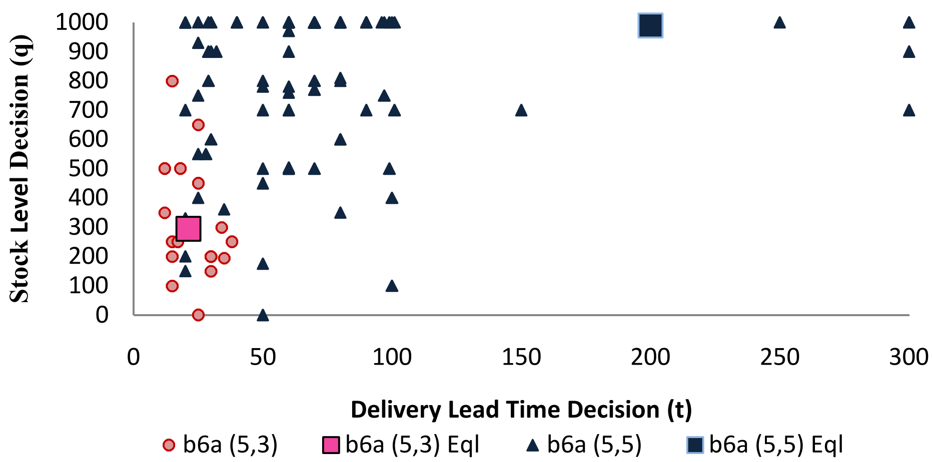



Figure 5.3. Decisions in Experiments b1a, b4a and b6a

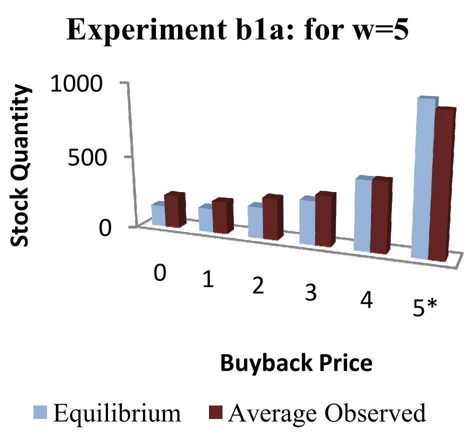
We observe that although the model's qualitative predictions hold, the data has deviations from model's quantitative equilibrium predictions. Table 5.13 shows the predicted equilibrium values (in "Eql." column), mean and median values of the observed data (in "Avg." and "Med." columns) for decision variables $t$ and $q$. The table shows the p-values obtained from testing the null hypothesis that the median difference between the observed values and the predicted equilibrium value of the operational decision in each experiment for stated $(w, b)$ is zero. As indicated by the p-values, for most experiments the median difference between the predicted equilibrium value and the observed data is found to be statistically significant by the Wilcoxon Signed Rank Test.

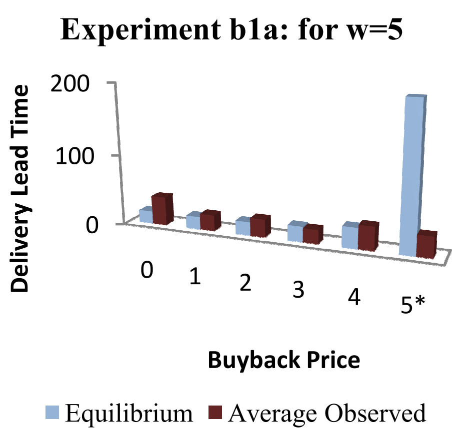
Table 5.13. Comparing the Equilibrium Predictions with the Observed Data

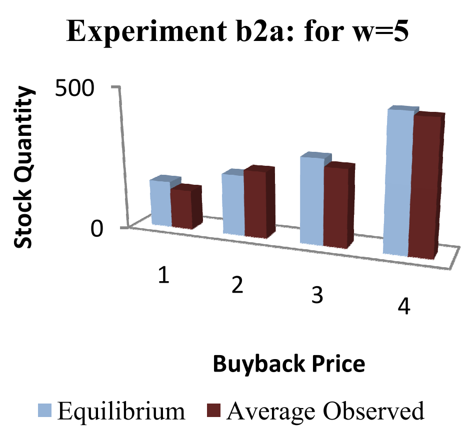
| Exp. | (w, b) | **Delivery Lead Time *t*** | | | **Stocking Level *q*** | | | **p-values** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | **WRS test** | | **KS test** |
| | | Eql. | Avg. | Med. | Eql. | Avg. | Med. | $\boldsymbol{t}$ | $\boldsymbol{q}$ | $(\boldsymbol{t}, \boldsymbol{q})$ |
| b1a | 5,4 | 28.70 | 32.80 | 30.00 | 466.70 | 470.48 | 500.00 | 0.37 | 0.62 | 1.00 |
| b1a | 5,5 | 200.00 | 29.00 | 29.00 | 990.00 | 931.67 | 1000.00 | **0.01** | 0.91 | 1.00 |
| b2a | 5,2 | 18.80 | 33.81 | 37.50 | 211.70 | 231.94 | 250.00 | **0.00** | 0.68 | **0.00** |
| b3a | 3,2 | 38.00 | 41.97 | 32.50 | 716.20 | 619.11 | 650.00 | **0.03** | **0.00** | **0.00** |
| b4a | 5,4 | 21.90 | 45.90 | 45.90 | 334.20 | 488.25 | 488.25 | 0.14 | **0.01** | **0.00** |
| b4a | 5,5 | 100.00 | 20.00 | 20.00 | 920.00 | 850.00 | 850.00 | 0.16 | 0.66 | 1.00 |
| b5a | 5,3 | 4.30 | 7.79 | 5.00 | 305.70 | 454.00 | 400.00 | **0.01** | **0.00** | **0.00** |
| b6a | 5,5 | 200.00 | 73.70 | 60.00 | 990.00 | 795.79 | 900.00 | **0.00** | **0.00** | **0.00** |
| b6b | 5,3 | 20.80 | 26.59 | 20.00 | 321.80 | 264.39 | 307.50 | **0.01** | **0.01** | **0.00** |

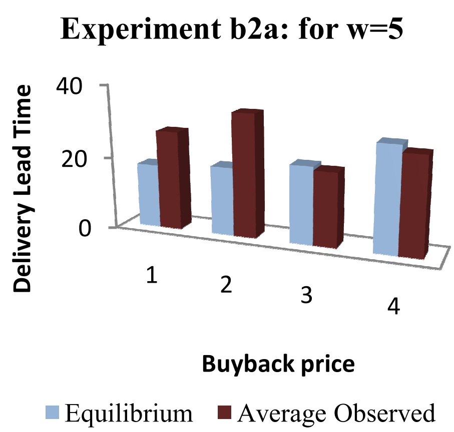
The table above also shows the p-values obtained from two-dimensional Kolmogrov-Smirtov test, which we used to test the null hypothesis that the observed values and the predicted equilibrium values of the operational decisions in each experiment for stated $(w, b)$ come from the same distribution. For most of the experiments, we find that the distributions of observed and predicted operational decisions are significantly different.

In general, manufacturers set higher delivery lead time than the model's prediction when the predicted level is low, and lower delivery lead time than the model's prediction when the predicted level is high. In general, retailers set lower stocking levels than the model's prediction when the predicted level is high and higher stocking levels than the model's prediction when the predicted level is low. It seems that the subjects do not prefer to choose very low and very high values, but instead they prefer values that are more moderate. The behavior of subjects' setting moderate values looks similar to "pull to center effect" (Bostian et al. 2008).



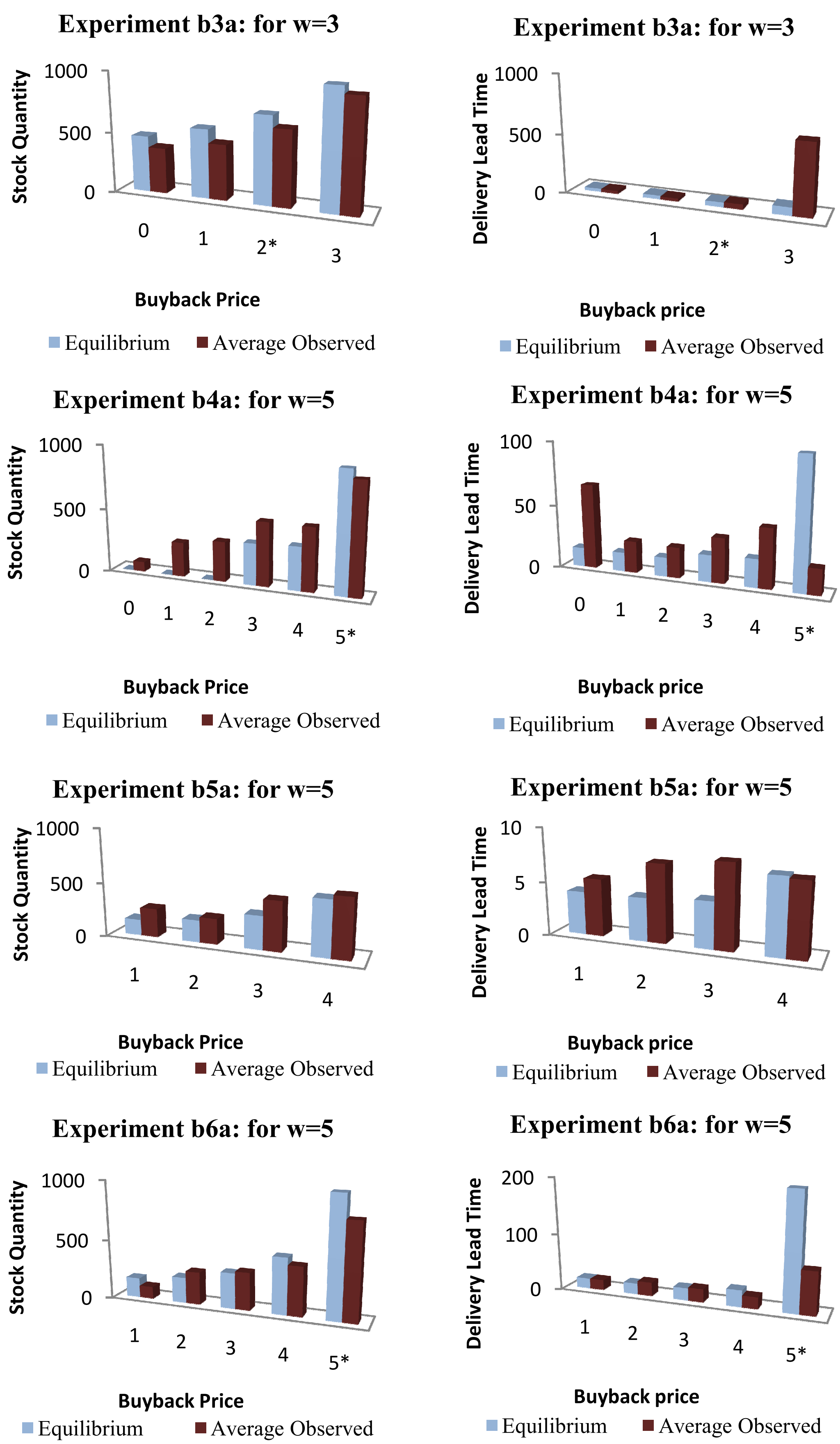



Figure 5.4. Equilibrium vs. Average Observed Decision

Figure 5.4 compares the average observed stage II decisions with equilibrium values for every buyback price set at stage I. For each experiment, we used only the data in which the wholesale price was set as the theoretical prediction. The theoretical optimal buyback prices are marked with an asterix[9]. We observe that there exist deviations from equilibrium values at this level as well.

According to our model, in a given experimental setting, for a fixed wholesale price, when buyback price increases, the retailer's stock level and the manufacturer's delivery lead time increase. As seen in Figure 5.4, our stock level data is almost consistent with this qualitative prediction of the model; however, our delivery lead time data is not. Average delivery lead time is higher than predicted for low buyback prices and lower than predicted for high buyback prices, in general. The manufacturer subjects do not prefer a very short delivery lead time, because the direct channel cost caused by a short delivery lead time is deterministic; whereas the demand of direct channel is not known. It depends on the retailer's decision and on the realization of the total random demand. Instead of risking themselves with a high uncertain payoff, the manufacturer subjects seem to prefer a lower yet more certain payoff. Risk and loss aversion might be reasons for this behavior. The manufacturer subjects do not prefer a very high delivery lead time; this is probably because the manufacturers do not prefer to depend only on the retailer's good judgment. If the retailer stocks low quantity, there will be lost customers and the manufacturer might capture some of those with the direct channel. Another factor might be the *endowment effect:* As the manufacturer "owns" the direct channel, he places a higher value on this channel than what would be rational.

These observations suggest that the analytical model of Gökduman and Kaya (2009) can be used to predict the characteristics of the decisions and the changes in the decisions when the manufacturer shifts from one dual channel strategy to another. However, the subjects' decisions have significant deviations from the model's quantitative predictions. Thus, the quantitative predictions of the model should not be used directly in decision-making in a real business environment.

[9] In some of the cases, we could not mark the optimal buyback price. Because this buyback price is not selected by the decision-makers. Thus, there exists no observed data for them.

#### 5.2.2.2. Learning in the Operational Decisions Game

Here, we again focus on the stage II decisions in order to analyze if the subjects learned how to make better decisions over time. We first controlled if there is dispersion in the decisions of the subjects in each experiment. We calculated the dispersion by multivariate standard deviation normalized by the mean values. The related formula is:

$$\sqrt{\frac{\sum_{i=1}^{n}((t_i-\bar{t})/\bar{t})^2+\sum_{i=1}^{n}((q_i-\bar{q})/\bar{q})^2}{n-1}}$$

where $(t_i, q_i)$ shows a data point representing the stage II decisions of a given manufacturer-retailer couple, $n$ is the number of observations (number of data points), and $\bar{t}$ and $\bar{q}$ are the means of the delivery lead time and stocking level decisions, respectively. We divide the deviations by their respective mean values for normalization. Normalization prevents the stocking level $(q_i)$ values, which are considerably larger, to dominate the delivery lead time $(t_i)$ values.

We find that operational decisions data exhibits significant dispersion. We expect that the subjects would search better strategies during the game. If so, the subjects would learn how to make better decisions over time, in which case the dispersion in their decisions would decrease and the mean of their decisions would move towards the Nash equilibrium predicted by the model. However, as shown in Figure 5.5, the dispersion measure increased from first half to second for most of the experiments. Dispersion is due to heterogeneity of subjects and their trying different decisions over the course of the experiments.

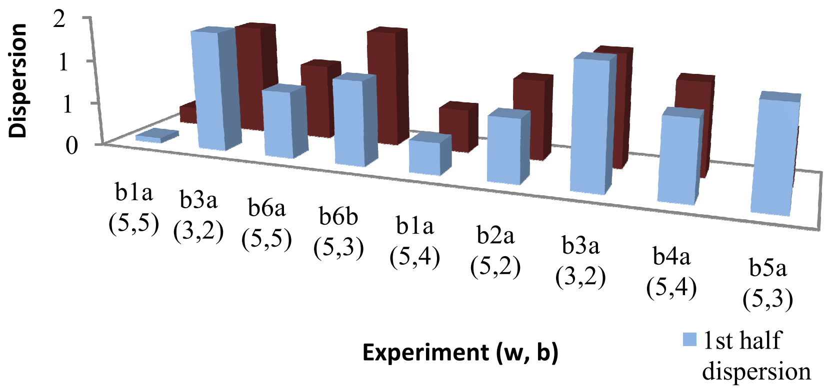



Figure 5.5. Comparison of Dispersion in the Two Halves of the Experiments

Second, we analyzed if the decisions in the first half and the second half of each experiment come from the same distribution or not. As the p-values in Table 5.14 indicate, for most of the experiments, we cannot reject the null hypothesis that the decisions in the first and the second half of an experiment are drawn from the same population by Kolmogrov-Smirnov (KS) and Wilcoxon Rank-Sum (WRS) tests. For one-dimensional KS test, we tested for each decision variable $t$ and $q$ separately; for the two dimensional test, we tested the $(t, q)$ decisions as a couple. In addition, as shown in the table, the average decisions in the two halves do not indicate a consistent move towards the equilibrium values.

Table 5.14. Comparing the Stage II Decisions in the Two Halves of Each Experiment

| | | | | | | | | **p-values** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp. | $(w, b)$ | **Delivery Lead Time $t$** | | | **Stock Level $q$** | | | **KS test** | | | **WRS test** | |
| | | Eql. | 1st Half Avg. | 2nd Half Avg. | Eql. | 1st Half Avg. | 2nd Half Avg. | $\boldsymbol{t}$ | $\boldsymbol{q}$ | $(\boldsymbol{t}, \boldsymbol{q})$ | $\boldsymbol{t}$ | $\boldsymbol{q}$ |
| b1a | 5,4 | 28.70 | 27.08 | 39.00 | 466.70 | 513.08 | 424.33 | 0.31 | 0.49 | 0.35 | **0.03** | 0.14 |
| b1a | 5,5 | 200.00 | 29.00 | 29.00 | 990.00 | 966.67 | 896.67 | 1.00 | 1.00 | 0.99 | 1.00 | 0.80 |
| b2a | 5,2 | 18.80 | 33.13 | 34.50 | 211.70 | 288.75 | 175.13 | 0.96 | 0.27 | 0.28 | 0.91 | 0.14 |
| b3a | 3,2 | 38.00 | 39.89 | 44.05 | 716.20 | 650.24 | 587.97 | 0.55 | 0.35 | 0.30 | 0.15 | **0.05** |
| b4a | 5,4 | 21.90 | 48.20 | 43.60 | 334.20 | 570.00 | 406.50 | 0.76 | 0.06 | 0.30 | 0.39 | 0.14 |
| b4a | 5,5 | 100.00 | 20.00 | 20.00 | 920.00 | 1000.00 | 700.00 | N/A | N/A | N/A | 1.00 | 0.32 |
| b5a | 5,3 | 4.30 | 10.60 | 4.79 | 305.70 | 460.00 | 447.57 | 0.09 | 0.84 | 0.21 | **0.02** | 0.77 |
| b6a | 5,5 | 200.00 | 61.52 | 86.16 | 990.00 | 760.41 | 831.96 | **0.05** | 0.16 | 0.13 | **0.04** | 0.35 |
| b6b | 5,3 | 20.80 | 29.46 | 23.72 | 321.80 | 320.86 | 207.93 | 0.16 | **0.01** | **0.03** | 0.13 | **0.02** |

Third, we analyzed whether the decisions in each experiment converge to the Nash equilibrium or not. We measured the distances of decisions in the first half and the second half of each experiment to the theoretical Nash equilibrium in order to analyze if there is a significant move towards the predicted equilibrium value. We tested the null hypothesis that the distances of the decisions in the two halves of an experiment are drawn from the same population. As shown in Table 5.15, for most of the experiments, we cannot reject the null hypothesis by one-dimensional Kolmogrov-Smirnov (KS) and Wilcoxon Rank-Sum (WRS) tests. In addition, the average distances in the two halves do not indicate a consistent improvement. Thus, we cannot say that the decisions move towards the equilibrium value, in general

Table 5.15. Comparing the Distances of Stage II Decisions in the Two Halves of Each Experiment

| | | **Distance of Delivery Lead Time $t$** | | | **Distance of Stock Level $q$** | | | **p-values** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | **KS test** | | **WRS test** | |
| Exp. | $(w, b)$ | Eql. | 1st Half Avg. | 2nd Half Avg. | Eql. | 1st Half Avg. | 2nd Half Avg. | $t$ | $q$ | $t$ | $q$ |
| b1a | 5,4 | 28.70 | 6.67 | 11.87 | 466.70 | 82.30 | 95.12 | 0.83 | 0.99 | 0.96 | 0.96 |
| b1a | 5,5 | 200.00 | 171.00 | 171.00 | 990.00 | 36.67 | 106.67 | 1.00 | 1.00 | 1.00 | 1.00 |
| b2a | 5,2 | 18.80 | 15.28 | 16.40 | 211.70 | 180.40 | 105.73 | 0.63 | 0.27 | 0.83 | 0.07 |
| b3a | 3,2 | 38.00 | 24.59 | 22.16 | 716.20 | 98.62 | 139.11 | 1.00 | 0.89 | 0.83 | 0.30 |
| b4a | 5,4 | 21.90 | 31.80 | 30.78 | 334.20 | 266.32 | 145.98 | 0.99 | 0.16 | 0.76 | 0.14 |
| b4a | 5,5 | 100.00 | 80.00 | 80.00 | 920.00 | 80.00 | 220.00 | N/A | 1.00 | N/A | 0.32 |
| b5a | 5,3 | 4.30 | 6.42 | 1.31 | 305.70 | 175.82 | 159.41 | 0.09 | 0.84 | 0.24 | 0.61 |
| b6a | 5,5 | 200.00 | 140.65 | 131.62 | 990.00 | 238.67 | 167.73 | 0.15 | 0.16 | **0.05** | 0.27 |
| b6b | 5,3 | 20.80 | 11.94 | 6.66 | 321.80 | 172.31 | 246.93 | **0.04** | **0.01** | **0.01** | **0.00** |

Experiment b6b turned out to be the only one that indicates some difference in the distance measure of the two halves data. Next, we check whether this difference is in the desired direction (i.e., reduced distance to equilibrium). In Figure 5.6 and Figure 5.7, we provide the histogram plots of distances of decisions to equilibrium. These plots indicate that the $t$ decisions are improved, but the $q$ decisions are not improved.

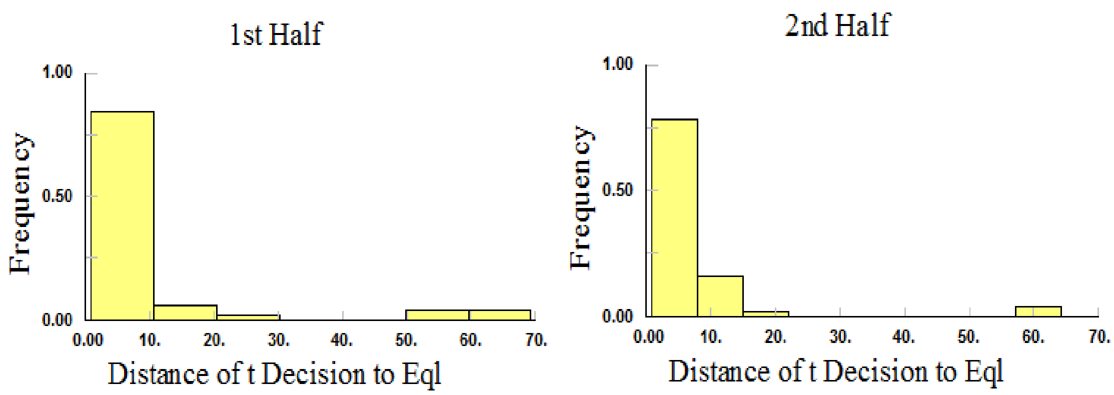



Figure 5.6. Histogram of Distances of Delivery Lead Time Decisions to Equilibrium in Experiment b6b

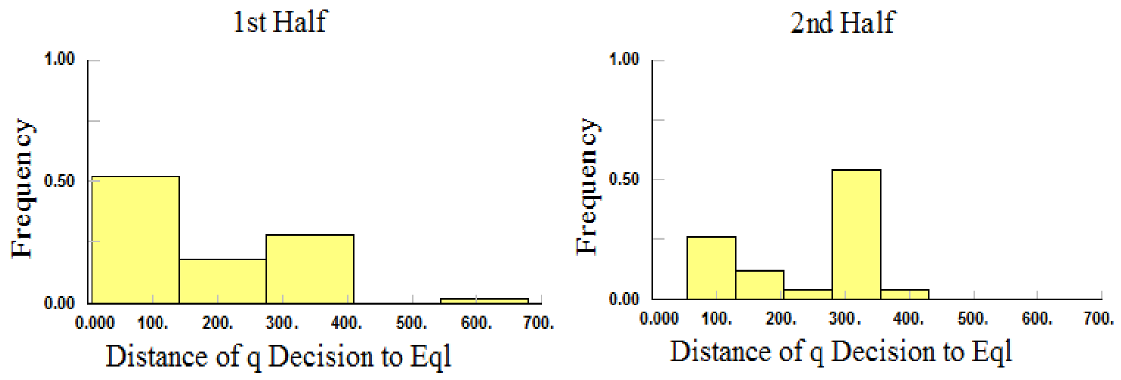



Figure 5.7. Histogram of Distances of Stock Level Decisions to Equilibrium in Experiment b6b

In conclusion, similar to the wholesale price experiments, we could not found indication of learning in the buyback experiments.

#### 5.2.2.3. Effect of Experiment Type on Operational Decisions

We are interested in determining how the experiment type (i.e., w & b setting, given-w & b-setting, given w &b) affects the outcome of the stage II operational decisions game. To this end, we compare the subject groups' behavior in the experiments with different experiment types when all other parameters are the same. In theory, a given wholesale price and buyback price, whether they are chosen by a human decision-maker (manufacturer) or exogenously given, should result in the same operational decisions at stage II game. In order to analyze, if there exists any difference, we compared the operational decisions from w & b setting experiments, given-w & b-setting experiments, and given w & b experiments for specified wholesale and buyback prices. In other words, we aim to find whether the manufacturer's determination of the contract parameters at stage I makes a difference in stage II outcome or not.

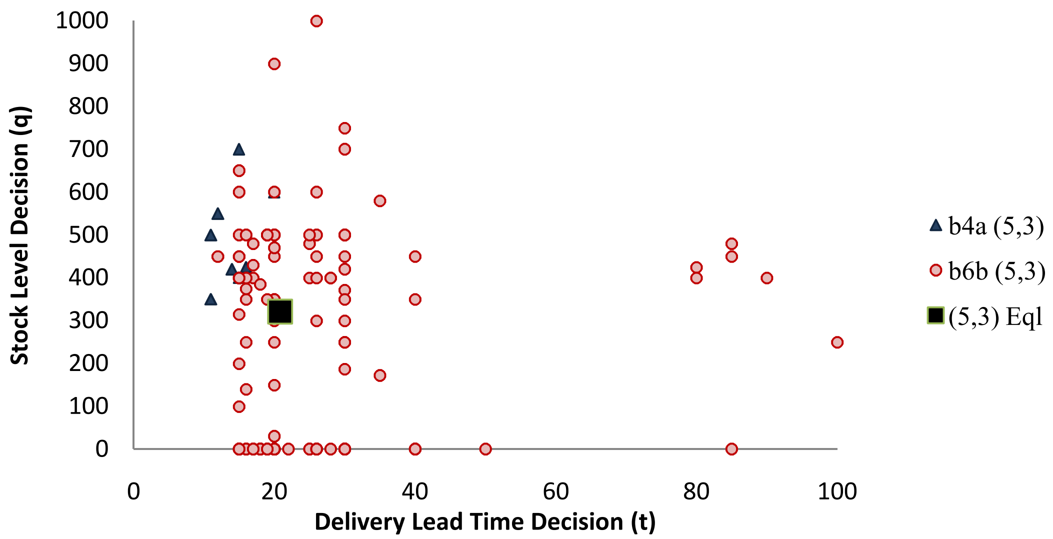



Figure 5.8. Comparison of Operational Decisions in w & b Setting and Given w & b Experiments

We detected some differences, particularly in the $t$ decisions. For example, Figure 5.8 compares the operational decisions between experiment b4a (w & b setting) and b6b (given w & b) for ($w$=5, $b$=3) data. Visual inspection suggests that there might be a difference between these two distributions. When we tested the data statistically, we obtained a p-value close to 0 for both $q$ and $t$ decisions by Wilcoxon Rank-Sum test. Thus, we rejected our null hypothesis that the decisions in the two experiments come from the same distribution.

We also compared the operational decisions in experiment b3a and b6a (given-w & b-setting) with b1a and b2a (w & b setting) for the same wholesale price and buyback price pairs. Related p-values are provided in Table 5.16. For almost all comparisons, we cannot reject the null hypothesis that the stock level decisions in the two experiments come from the same distribution by Wilcoxon Rank-Sum test. Hence, it seems like the retailers did not care much about whether the contract parameters were exogenously given, or set by the manufacturer. However, we reject the null hypothesis that the delivery lead time decisions in the two experiments come from the same distribution in 8 of the 14 comparisons. Thus, the manufacturers seem to care about the difference in the experiment type while making their delivery lead time decision.

Table 5.16. Comparing w & b Setting Experiments with Given-w & b-Setting Experiments

| | $(w, b)$ | b3a: $t$ comparison p-value | b3a: $q$ comparison p-value |
|---|---|---|---|
| b1a | 3,0 | **0.00** | 0.95 |
| | 3,1 | 0.59 | 0.61 |
| | 3,2 | 0.19 | 0.72 |
| b2a | 3,1 | 0.60 | 0.21 |
| | 3,3 | **0.05** | 0.06 |

| | $(w, b)$ | b6a: $t$ comparison p-value | b6a: $q$ comparison p-value |
|---|---|---|---|
| b1a | 5,1 | **0.02** | 0.33 |
| | 5,2 | 0.92 | 0.46 |
| | 5,3 | 0.20 | 0.27 |
| | 5,4 | **0.00** | **0.05** |
| | 5,5 | **0.00** | 0.23 |
| b2a | 5,1 | **0.05** | 0.37 |
| | 5,2 | **0.02** | 0.96 |
| | 5,3 | 0.47 | 0.96 |
| | 5,4 | **0.02** | 0.41 |

#### 5.2.2.4. Effect of Buyback Price on Operational Decisions

We are interested in determining how the manufacturer's buyback price decision affects the outcome of the stage II operational decisions game. To this end, we compared the stage II results by the buyback price in given-w & b-setting experiments (experiments b3a and b6a). We do not present the results from w & b setting experiments because they yield a low number of data for any $(w, b)$ pair.

Figure 5.9 compares the results by the buyback price (0 versus 2, and 1 versus 3) for experiment b3a. We observe that higher buyback prices usually lead to longer delivery lead times and higher stock levels. This observation is consistent with the analytical model's predictions. Note that our overall observations regarding dispersion and deviation from equilibrium are present in these figures.

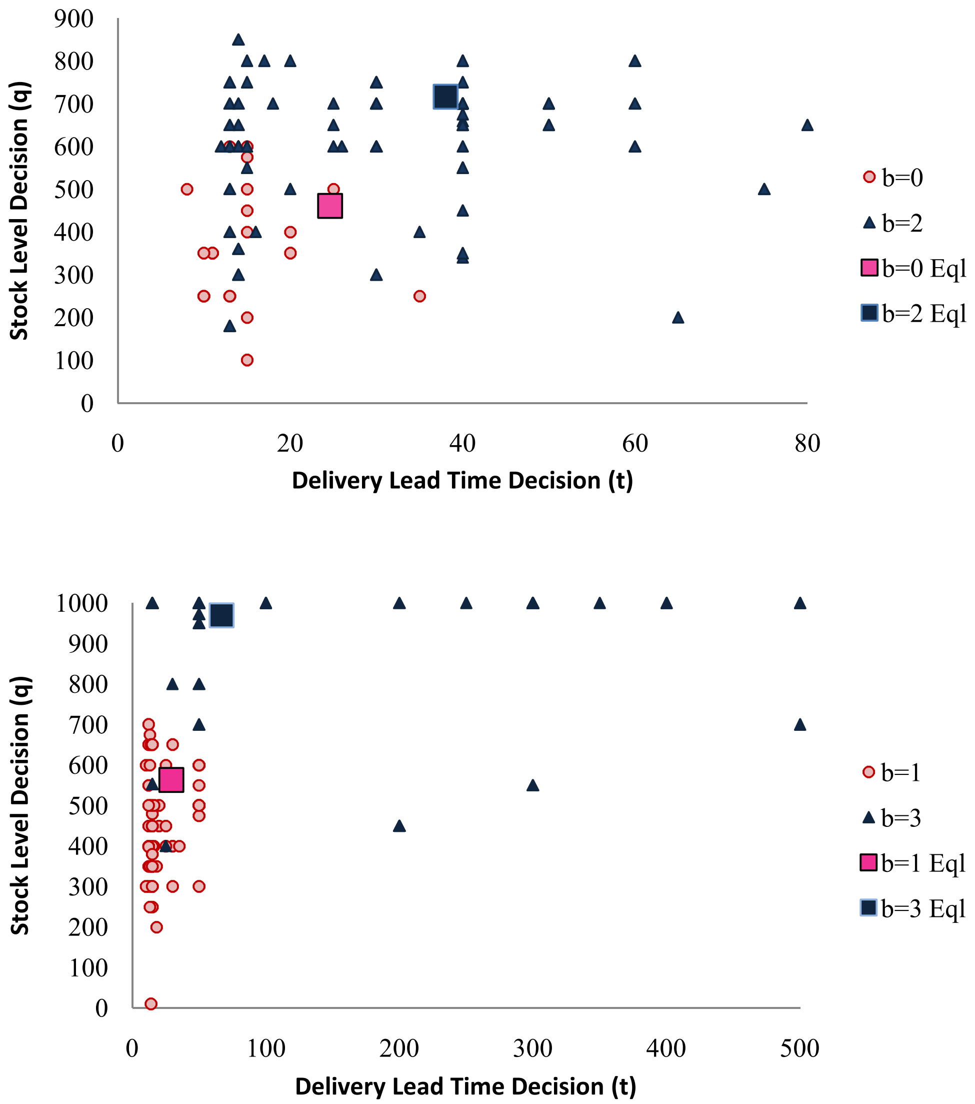



Figure 5.9. Decisions by the Buyback Prices in Experiment b3a

In order to compare the stage II results by the buyback price statistically, we conducted two-dimensional Kolmogrov-Smirnov tests. We tested the null hypothesis that the $(t, q)$ decisions by the buyback prices are drawn from the same population. As presented in Table 5.17 and Table 5.18, the subjects' behavior is dependent on the buyback price set at stage I.

Table 5.17. Comparison of the Stage II Decisions by the Buyback Price in Experiment b3a

| **Exp b3a** | ***b*=0** | ***b*=1** | ***b*=2** | ***b*=3** |
|---|---|---|---|---|
| ***b*=0** | N/A | 0.07 | **0.00** | **0.00** |
| ***b*=1** | 0.07 | N/A | **0.00** | **0.00** |
| ***b*=2** | **0.00** | **0.00** | N/A | **0.00** |
| ***b*=3** | **0.00** | **0.00** | **0.00** | N/A |

Table 5.18. Comparison of the Stage II Decisions by the Buyback Price in Experiment b6a

| **Exp b6a** | ***b*=1** | ***b*=2** | ***b*=3** | ***b*=4** | ***b*=5** |
|---|---|---|---|---|---|
| ***b*=1** | N/A | **0.02** | **0.00** | **0.00** | **0.00** |
| ***b*=2** | **0.02** | N/A | 0.31 | **0.00** | **0.00** |
| ***b*=3** | **0.00** | 0.31 | N/A | **0.04** | **0.00** |
| ***b*=4** | **0.00** | **0.00** | **0.04** | N/A | 0.00 |
| ***b*=5** | **0.00** | **0.00** | **0.00** | **0.00** | N/A |

### 5.2.3. Results in the Stage I Decisions

We analyze stage I decisions in two parts. First, we check if the manufacturer subjects chose the theoretically optimal stage I decisions or not. Second, we check if there is any learning in the stage I decisions.

#### 5.2.3.1. Comparing the Theoretical Optimum Predictions and Observed Data

Theory assumes that the manufacturer subjects can "foresee" the outcome of the stage II game, and set the stage I decisions (i.e., the contract parameters $w$ and $b$) accordingly. Given our experiments' complex setting, and high uncertainty due to random total demand, it would not be easy for the manufacturers to do that. Hence, we are interested in comparing their decisions with the theoretical predictions.

Figure 5.10 presents the $(w, b)$ choices of subjects in the w & b setting experiments. The figure illustrates the number of times that a specific wholesale price and buyback price pair is selected in each experiment. Theoretical optimal $(w, b)$ values of each experiment are marked with an asterix. In general, we observe that the manufacturer subjects not necessarily choose the theoretically optimal $w$ and $b$ values when they are setting both $w$ and $b$. The subjects usually choose $w$ values that are close to the theoretical optimal, whereas the chosen $b$ values are well below the optimal. As we will discuss later, this tendency of the manufacturers caused suboptimal profits for both firms, on average.

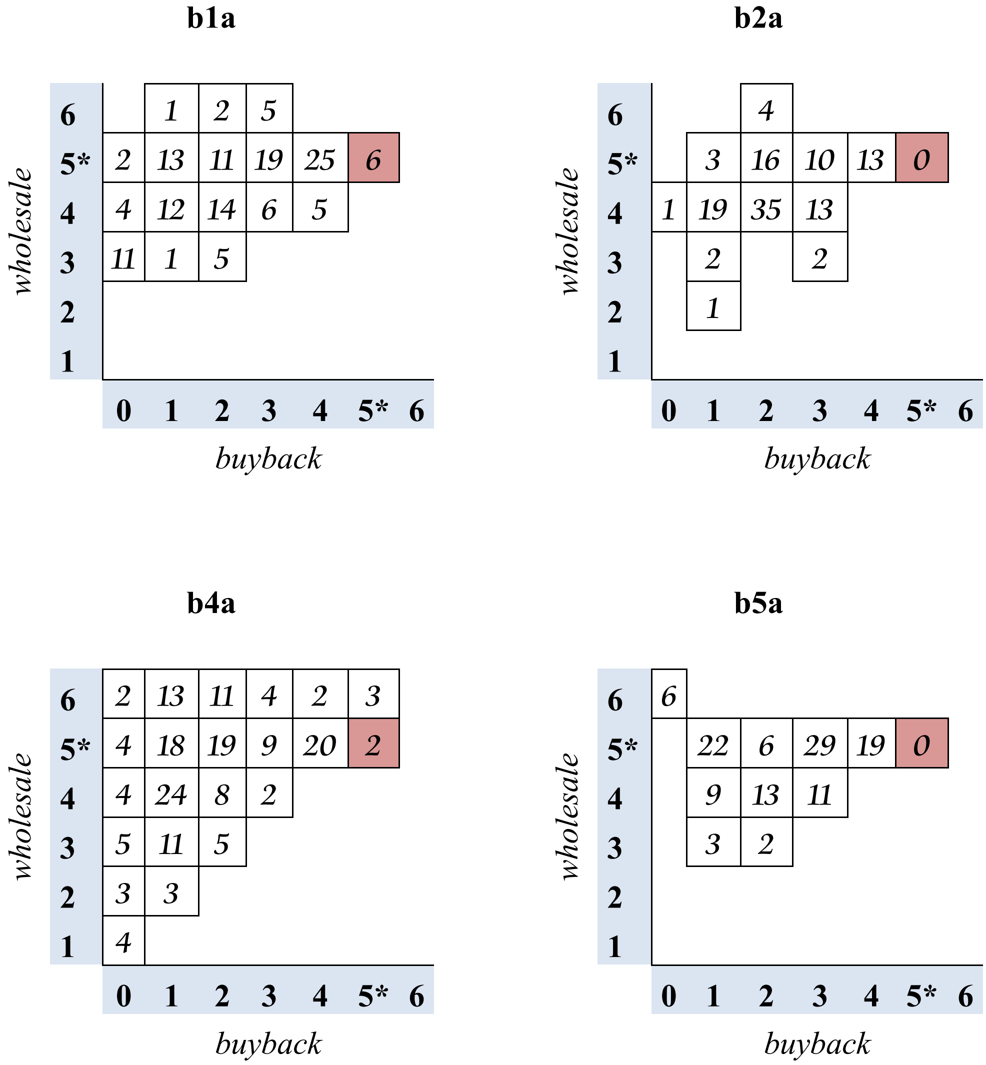



Figure 5.10. Comparison of $(w, b)$ Choice for w & b Setting Experiments

Figure 5.11 presents the results for the given-w and b-setting experiments. Here we observe that the subjects did set the theoretically optimal buyback price most frequently, when $w$ is not a decision.

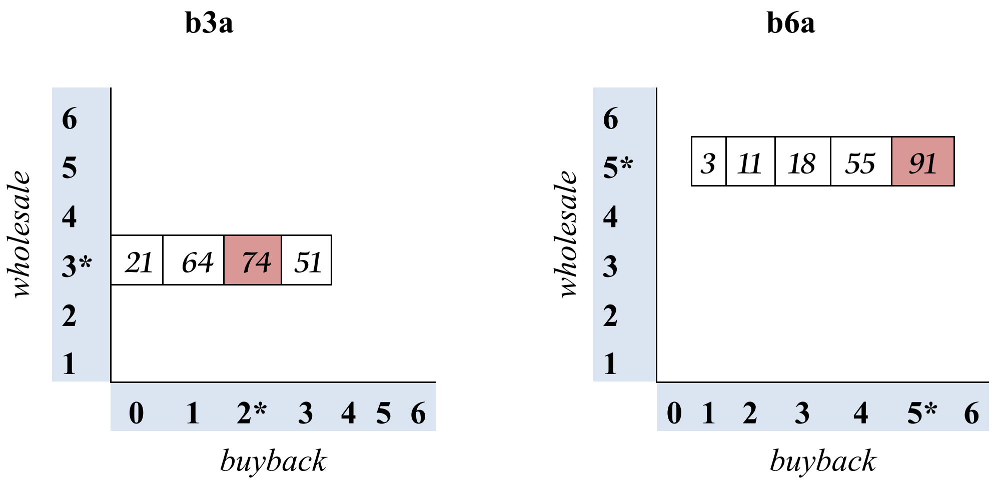



Figure 5.11. Comparison of $(w, b)$ Choice for Given-w & b-Setting Experiments

The "theoretical optimal" $(w, b)$ couple assumes that the players will play the Nash equilibrium at stage II. However, we know that their choices deviate significantly from the equilibrium predictions. Hence, the theoretical optimum couple may not be the practical optimum to set at stage I. We are interested in comparing the subjects' choices with the theoretical optimum and the practical optimum $(w, b)$ couples.

Table 5.19 compares manufacturer's average observed profit with theoretical optimum $(w, b)$ couple, with the practical optimum $(w, b)$ couple (i.e., the observed optimal $(w, b)$ couple that resulted in the highest observed manufacturer's profit) and with the most frequently selected $(w, b)$ couple.

First, as we mentioned above, the profit results show that the theoretical optimal $(w, b)$ couple is not the practical optimal $(w, b)$ for most of the experiments. Only in experiment b1a, the theoretical optimal $(w, b)$ couple is also the practical optimal, which provided more profit than the model predicts. Second, in all of the experiments, the most frequently selected $(w, b)$ couple is different from the theoretical optimal. Third, in the three of the four experiments, the $(w, b)$ couple that the subjects chose most frequently provided less profit than the average realized profit of the practical optimal $(w, b)$. In experiment b5a, subjects selected the most profitable $(w, b)$ couple the most frequently. In general, the subjects are not successful in selecting either the theoretical optimal or the practical optimal $(w, b)$ couple the most.

Table 5.19. Manufacturer's Profit Comparison for w & b Setting Experiments

| Exp. | **Theoretical Optimal $(w, b)$** | | **Practical Optimal $(w, b)$** | | **Most Selected $(w, b)$** | |
|---|---|---|---|---|---|---|
| | $(w, b)$ | Manufacturer's Average Profit | $(w, b)$ | Manufacturer's Average Profit | $(w, b)$ | Manufacturer's Average Profit |
| b1a | 5,5 | 2857.50 | 5,5 | 2857.50 | 5,4 | 2184.16 |
| b2a | 5,5 | N/A | 5,4 | 2074.77 | 4,2 | 1482.03 |
| b4a | 5,5 | 2113.50 | 6,5 | 2862.67 | 4,1 | 2042.83 |
| b5a | 5,5 | N/A | 5,3 | 2617.97 | 5,3 | 2617.97 |

N/A*: not available

Next, we study whether the subjects selected the most profitable buyback price, for a specific wholesale price value (exogenously given in experiments 3a, 6a, and for $w$=5 data in experiments 1a, 2a, 4a, 5a). To do this, we compared the choice frequency of buyback prices and manufacturer's average observed profit with these buyback prices in all experiments except b6b. Figure 5.12 summarizes this comparison. Again, we observe that the subjects do not choose the most profitable buyback price in most of the experiments.

In conclusion, these analysis show that in general, the manufacturers can not anticipate the stage II decisions and set the stage I parameters accordingly in a dual channel environment with a buyback contract. Recall that in the wholesale price contract study, the manufacturers were somewhat successful in choosing the practical-optimal wholesale price at stage I. We believe that the introduction of the buyback price into the contract forces the limits of participants' cognitive abilities. The participants might have difficulty judging the effects of the two contract parameters $w$ and $b$ together. While the manufacturers are comfortable in setting high wholesale price, they are not as so when it comes to offering a high buyback price. This severely limits the potential gains from using a buyback contract. Hence, using a more sophisticated contract does not guarantee high increase in performance due to such mental limits. In fact, this may be one reason why simple contracts are preferred to more sophisticated ones in practice.

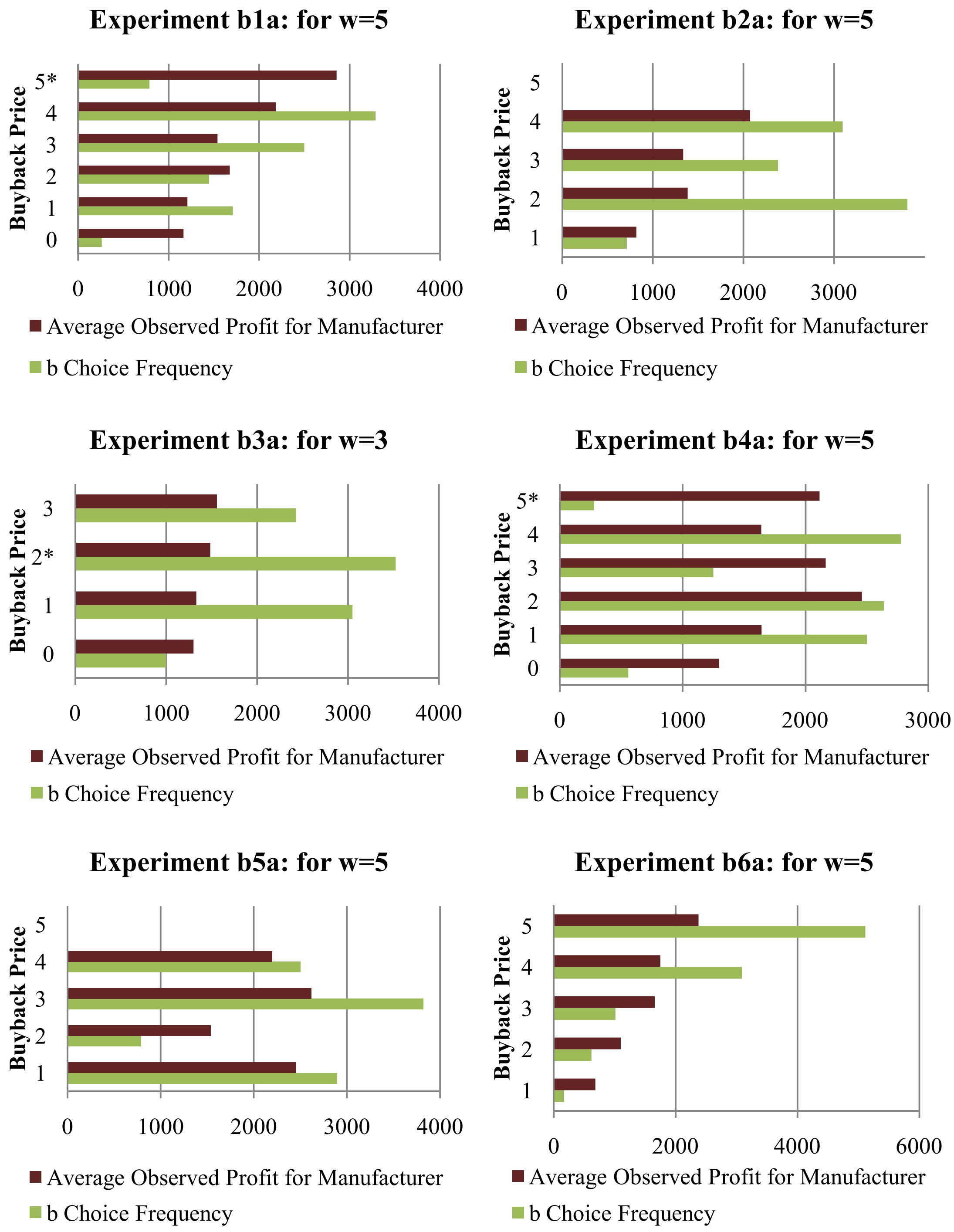



Figure 5.12. Comparison of Buyback Price Choice Frequency and Average Observed Profit

### 5.2.3.2. Learning in the Wholesale Price and Buyback Decisions

In section 5.2.2.2., we could not identify significant learning in stage II decisions. Here, we conduct a similar study regarding the manufacturer's wholesale price and buyback price decision at stage I.

For analyzing w & b setting experiments, we compared the wholesale price and buyback decisions in the first half with the decisions in the second half of each experiment by the two-dimensional Kolmogrov-Smirnov test. We tested the null hypothesis that the stage I decisions $(w, b)$ from the two halves of an experiment have identical distribution function. As indicated by the p-values in Table 5.20, we could not detect any significant difference between the decisions in the two halves of the stated experiments. Hence, we failed to find evidence regarding "learning" with this approach.

Table 5.20. Comparing the Stage I Decisions in the Two Halves of Each Experiment

| Exp. | Eql. $(\boldsymbol{w}, \boldsymbol{b})$ | Avg. $\boldsymbol{w}$ 1$^{st}$ Half | Avg. $\boldsymbol{w}$ 2$^{nd}$ Half | Avg. $\boldsymbol{b}$ 1$^{st}$ Half | Avg. $\boldsymbol{b}$ 2$^{nd}$ Half | p-value |
|---|---|---|---|---|---|---|
| b1a | (5,5) | 4.48 | 4.58 | 2.15 | 2.51 | 0.39 |
| b2a | (5,5) | 4.37 | 4.37 | 2.13 | 2.27 | 0.70 |
| b4a | (5,5) | 4.51 | 4.59 | 1.63 | 1.93 | 0.20 |
| b5a | (5,5) | 4.58 | 4.80 | 2.32 | 2.22 | 0.28 |

Table 5.21. Comparing the Buyback Price Decisions in the Two Halves of Each Experiment

| Exp. | Eql. $\boldsymbol{b}$ | Avg $\boldsymbol{b}$ of 1$^{st}$ Half | Avg. $\boldsymbol{b}$ of 2$^{nd}$ Half | p-value | |
|---|---|---|---|---|---|
| | | | | KS test | WRS test |
| b3a | 2 | 1.65 | 1.83 | 0.61 | 0.15 |
| b6a | 5 | 4.04 | 4.43 | 0.30 | **0.02** |

For the given-w & b-setting experiments, the only decision at stage I is the buyback price. We tested the null hypothesis that the buyback price decisions in the two halves of an experiment come from the same population. As summarized in Table 5.21, the Wilcoxon Rank-Sum (WRS) test detects significant difference between the two halves of experiment b6a. However, Kolmogorov-Smirnov test indicates no significant difference for the same experiment. Both tests fail to reject the null hypothesis of no difference for the other experiment, b3a.

Given these observations, we analyzed the buyback price decisions in experiment b6a in detail. Figure 5.13 shows that the average (over players) buyback price in experiment b6a increases over periods towards the theoretical optimal value $b$. This may indicate some learning.

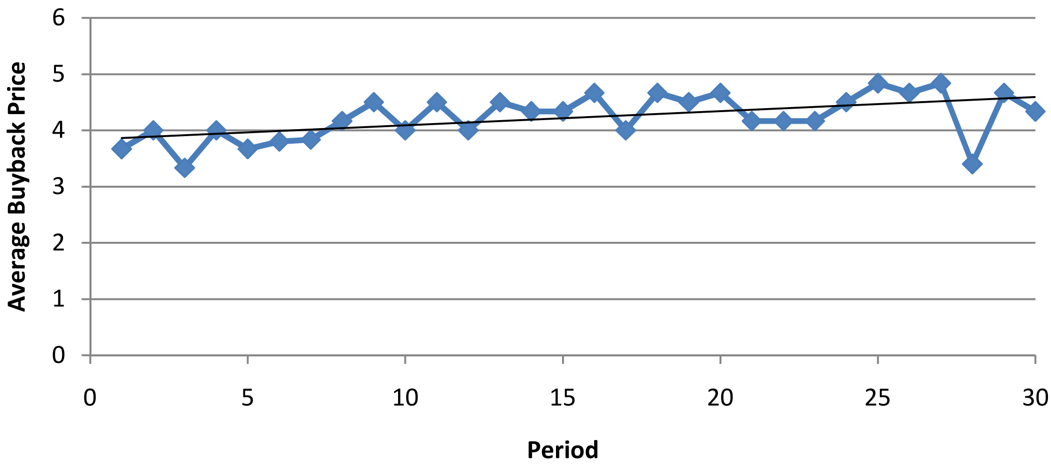



Figure 5.13. Average Buyback Price per Period in Experiment b6a

To find evidence of learning, we also tried an alternative approach. We analyzed if the buyback price for given-w & b-setting experiments converge to the theoretical optimum value or not. In order to check if there is a move in the direction of theoretical optimum value, we conducted Kolmogrov-Smirnov (KS) and Wilcoxon Rank-Sum (WRS) tests and compared the "distances" of buyback price decisions to the theoretical optimal $b$ value in the two halves of each experiment. We define "distance" as the absolute value of the difference between a data point and the theoretical optimal value. We tested the null hypothesis that the distances of buyback price decisions to the theoretical optimal $b$ value in the two halves of an experiment have identical distribution function.

Similar to our previous finding, the only significant difference we found was for experiment b6a, with Wilcoxon Rank-Sum test. The results are summarized in Table 5.22. In addition, as shown in the table, the average distances in the two halves do not indicate a consistent improvement. Thus, we cannot say that the decisions move towards the theoretical optimum values, in general.

Table 5.22. Comparing the Distances of Buyback Price Decisions in the Two Halves of Each Experiment

| | | 1st Half Distance | | 2nd Half Distance | | p-value | |
|---|---|---|---|---|---|---|---|
| Exp. | Eql. | Avg. | Std. Dev. | Avg. | Std. Dev. | **KS test** | **WRS test** |
| b3a | 2 | 0.73 | 0.64 | 0.76 | 0.61 | 1.00 | 0.69 |
| b6a | 5 | 0.96 | 1.09 | 0.57 | 0.82 | 0.30 | **0.02** |

Again, we focus on experiment b6a decisions where there is some indication of learning, i.e., statistically significant difference between the distance values. From the table above, we observe that the average and standard deviation of the distances are smaller in the second half of the experiment. Figure 5.14 compares the histogram plot of distances between the two halves also supporting this result. For this experiment, the subjects might have learned how to make better decisions over time.

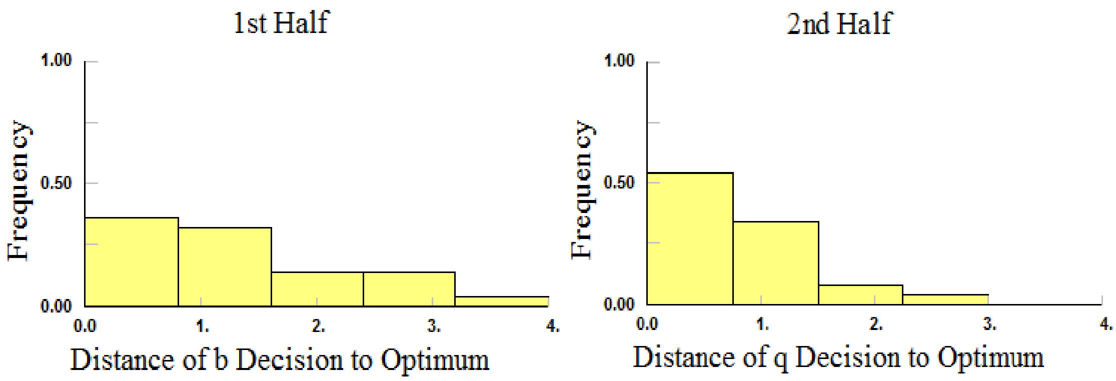



Figure 5.14. Histogram of Distances of Buyback Decisions to the Equilibrium in Experiment b6a

For experiment b6a, we analyzed the change in the manufacturer's profit and retailer's profit. Figure 5.15 shows that the manufacturer's average (over players) profit increases over periods. However, this is not supported statistically. Figure 5.16 shows that the retailer's average profit in experiment b6a increases over periods towards the theoretical optimal value (495). The increase in the retailer's average profit is found to be significant with a p-value of 0.01 and $R^2$ value of 0.197. Thus, for this experiment, the improvement of buyback decisions affects the retailer's profit the most.

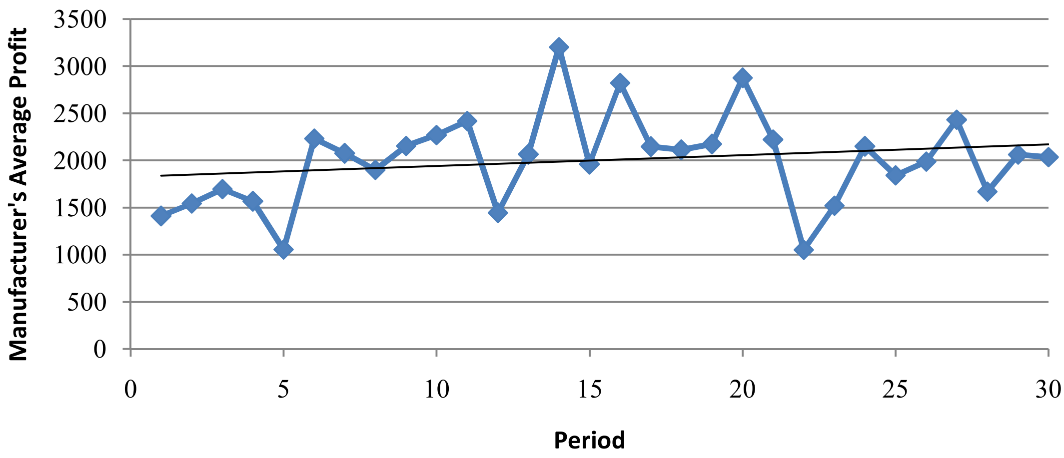



Figure 5.15. Manufacturer's Average Profit per Period in Experiment b6a

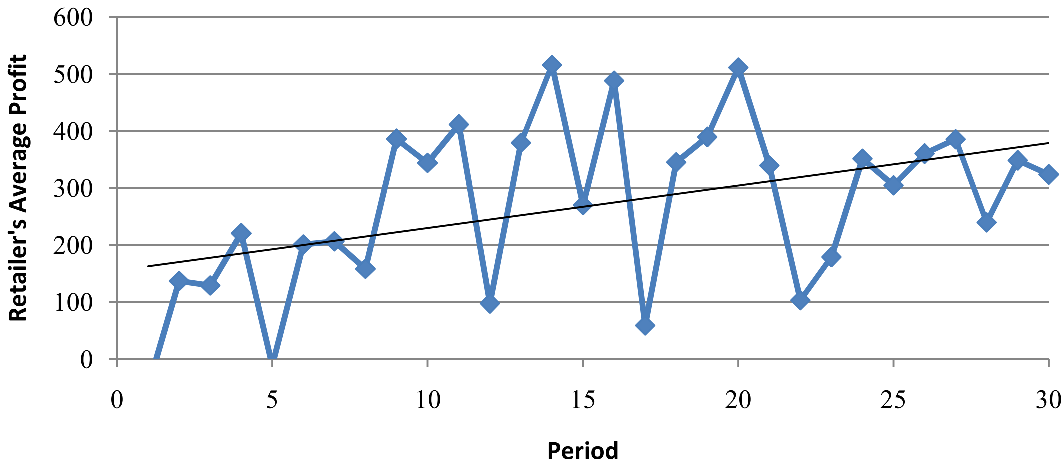



Figure 5.16. Retailer's Average Profit per Period in Experiment b6a

If the subjects learn how to make better decisions over periods, their profit should increase. To analyze whether there is a significant profit change, we tested the null hypothesis that the profits in the two halves of a given experiment come from the same distribution. We conducted our tests for the data that have the stated $(w, b)$ couples in Table 5.23 and Table 5.24 (for the manufacturer and the retailer respectively).

Table 5.23. Analyzing the Change in the Manufacturer’s Profit

| **Exp.** | **(w,b)** | **Manufacturer's Profit** | | | **p-value** | |
|---|---|---|---|---|---|---|
| | | Eql. | 1st Half Avg. | 2nd Half Avg. | **KS test** | **WRS test** |
| b1a | 5,4 | 2038.00 | 2431.00 | 1916.75 | 0.60 | 0.16 |
| b1a | 5,5 | 2503.00 | 2934.00 | 2781.00 | 1.00 | 0.51 |
| b2a | 5,2 | 1326.00 | 1613.13 | 1158.00 | 0.63 | 0.37 |
| b3a | 3,2 | 1713.00 | 1583.49 | 1384.38 | 0.72 | 0.23 |
| b4a | 5,4 | 2108.00 | 2020.70 | 1256.40 | 0.76 | 0.41 |
| b4a | 5,5 | 2520.00 | 4419.00 | -192.00 | N/A | 0.32 |
| b5a | 5,3 | 2257.00 | 2118.20 | 3153.43 | **0.04** | **0.01** |
| b6a | 5,5 | 2503.00 | 2553.96 | 2195.22 | 0.35 | 0.25 |
| b6b | 5,3 | 2171.00 | 1772.60 | 1476.21 | 0.06 | 0.14 |

The p-values in Table 5.23 indicate that manufacturer’s profit increases significantly only in experiment b5a. Contrary to our expectation, a comparison of the manufacturer’s average profits finds a decrease from the first half of the experiment to the second for most experiments. Hence, we could not find any support regarding the manufacturer’s learning.

Table 5.24. Analyzing the Change in the Retailer’s Profit

| **Exp.** | **(w,b)** | **Retailer's Profit** | | | **p-value** | |
|---|---|---|---|---|---|---|
| | | Eql. | 1st Half Avg. | 2nd Half Avg. | KS test | WRS test |
| b1a | 5,4 | 227.40 | 335.69 | 251.00 | 0.73 | 0.38 |
| b1a | 5,5 | 495.00 | 561.00 | 532.00 | 1.00 | 0.56 |
| b2a | 5,2 | 101.20 | 148.75 | 114.63 | 0.96 | 0.75 |
| b3a | 3,2 | 1062.00 | 959.92 | 855.70 | 1.00 | 0.63 |
| b4a | 5,4 | 144.60 | -194.80 | -177.30 | 0.99 | 0.68 |
| b4a | 5,5 | 460.00 | 547.00 | 34.00 | N/A | 0.32 |
| b5a | 5,3 | 125.30 | 76.00 | 337.21 | 0.22 | 0.08 |
| b6a | 5,5 | 495.00 | 491.41 | 423.56 | 0.23 | 0.26 |
| b6b | 5,3 | 47.97 | -237.77 | -94.60 | 0.05 | 0.06 |

Table 5.24 presents the same results for the retailer's profit. Again, we could not detect any significant change in the retailers' profit from first half to second half of the experiments, in general.

Next, we make a period-by-period comparison of the first and second half profits of the two firms. Figure 5.17 presents the results for experiment b6b, as an example. Each point in the figure represents the profit outcome of a manufacturer and a retailer at a single period of the experiment. Circles represent the first half data, whereas triangles represent the second half data. Visual inspection suggests that the profits of the firms have not improved from first half to second half of the experiment.

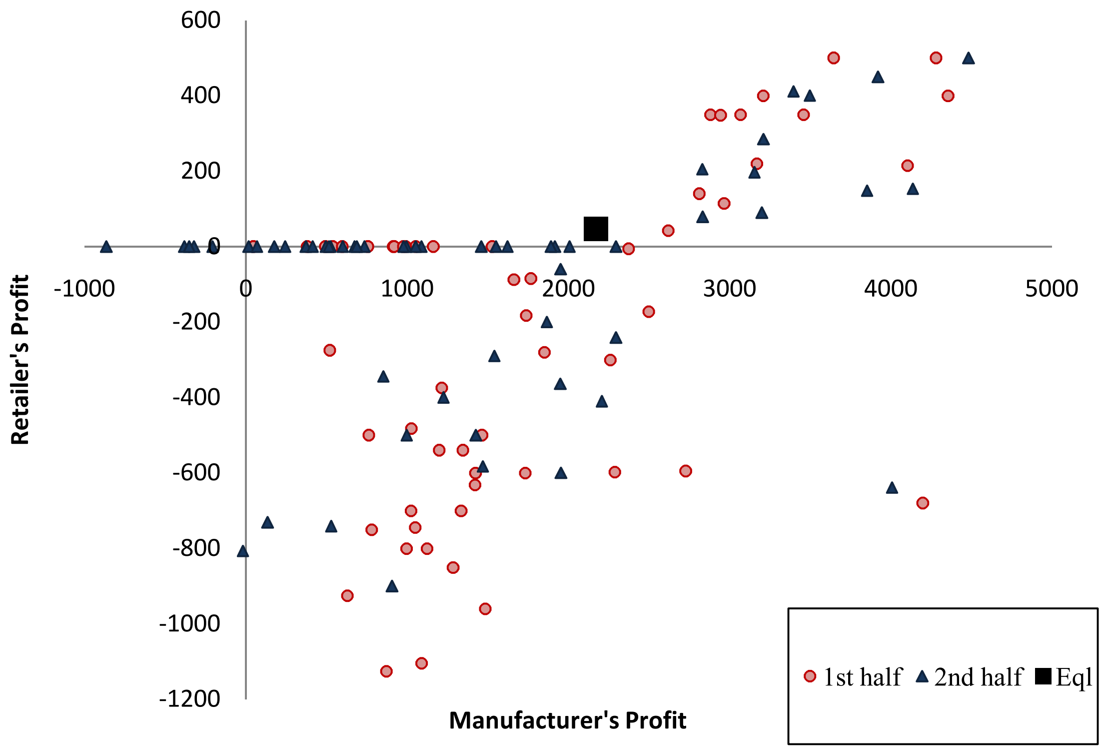



Figure 5.17. Comparison of the Manufacturer's and the Retailer's Profits in the Two Halves of Experiment b6b

This observation is supported by two-dimensional Kolmogrov-Smirnov tests as shown in Table 5.25 for selected $(w, b)$ couples. We cannot reject the null hypothesis that the profit outcomes of the manufacturer-retailer couples at each period come from the same distribution in the two halves of an experiment in all of the experiments.

Table 5.25. Analyzing the Change in the Manufacturer's and the Retailer's Profit

| Exp. | b1a | b1a | b2a | b3a | b4a | b5a | b6a | b6b |
|---|---|---|---|---|---|---|---|---|
| $(w, b)$ | 5,4 | 5,5 | 5,2 | 3,2 | 5,4 | 5,3 | 5,5 | 5,3 |
| KS test p-value | 0.41 | 0.99 | 0.73 | 0.59 | 0.67 | 0.09 | 0.39 | 0.07 |

Figure 5.17 also suggests a positive correlation between the manufacturer's and the retailer's observed profits. To check this relationship, we fitted a regression line by excluding the data points where the retailer's observed profit is zero (i.e., where the retailer opted out by stocking zero units).

Figure 5.18 represents this relationship. The significance of the relationship is close to 0, and $R^2$=0.531, a quite high value. The reason behind this strong relation is that both firms' observed profit depends critically on the realization of the random total demand.

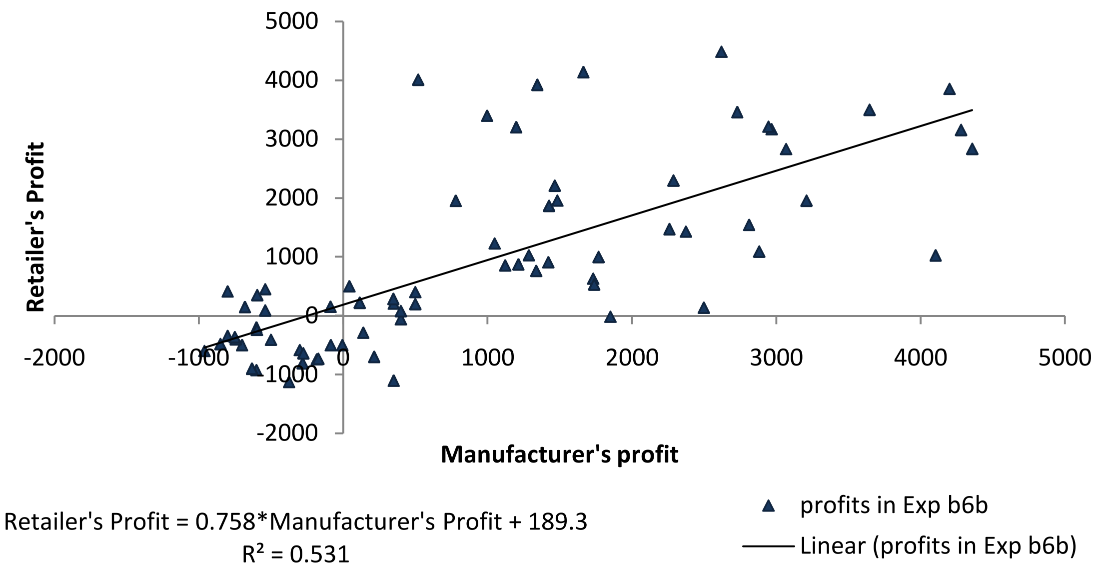



Figure 5.18. Relationship of the Manufacturer's and the Retailer's Profit in Experiment b6b

Table 5.26 presents the results of regression analysis between the manufacturer's and the retailer's observed profits for other experiments and $(w, b)$ couples statistically. All of the regression results are significant with relatively high $R^2$ values and p-values less than 0.01. The results reject the null hypothesis that there is no relationship between the manufacturer’s and the retailer’s profits.

Table 5.26. Relationship between the Manufacturer’s and the Retailer’s Profits

| Exp. | $(\boldsymbol{w}, \boldsymbol{b})$ | $R^2$ | p-value |
|---|---|---|---|
| b1a | 5,4 | 0.84 | 0.00 |
| b1a | 5,5 | 1.00 | 0.00 |
| b2a | 5,2 | 0.55 | 0.00 |
| b3a | 3,2 | 0.90 | 0.00 |
| b4a | 5,4 | 0.37 | 0.01 |
| b5a | 5,3 | 0.59 | 0.00 |
| b6a | 5,5 | 1.00 | 0.00 |
| b6b | 5,3 | 0.24 | 0.00 |

### 5.2.4. Other Analysis

Here we analyze the data to find out the trends (increase/decrease) over periods and correlations between decision variables.

First, we are concerned with how the average decisions (over players) change over periods to learn if there exists any significant trend. To this end, we conducted simple (with one independent variable) linear regression calculations and observed trends in certain period averages, as summarized in Table 5.27.

Table 5.27. Trends in Decisions over Periods

| | **Average Decision / Period** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Exp.** | $\boldsymbol{w}$ | $\boldsymbol{b}$ | $\boldsymbol{t}$ | $\boldsymbol{q}$ | $\boldsymbol{w-b}$ | **manufacturer's profit** | **retailer's profit** |
| b1a | | increasing | increasing | | decreasing | | |
| b2a | | | increasing | | | | |
| b3a | | | | | | decreasing | |
| b4a | | increasing | | decreasing | | | |
| b5a | increasing | | | | | | |
| b6a | | increasing | increasing | increasing | decreasing | | increasing |
| b6a | | | decreasing | decreasing | | | |

The changes in the stated variables are found to be statistically significant with a p-value less than 0.01. However, $R^2$ values are found to be less than 0.3 which shows that trend over periods is not the only significant factor in explaining the overall variation. In particular, we observe that there is some indication of buyback prices and delivery lead time decisions rising over time. This suggests that the manufacturers switched from their direct channel to retail channel over the course of the experiment.

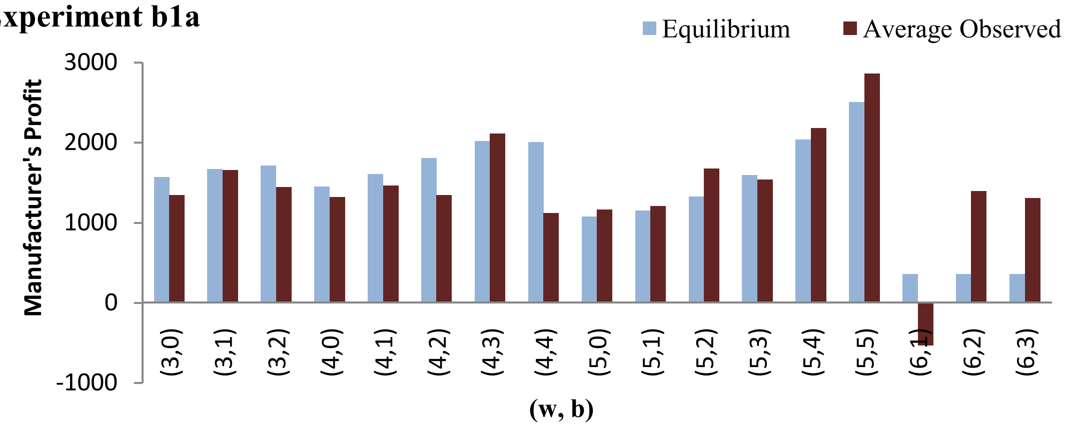
Second, we analyze the relationship between the variables in each experiment to find out the effect of decisions to each other, if any. To do this, we conducted a regression analysis of each variable on other by using the data from the same period in each experiment. We tested the null hypothesis that there is no relationship between the two variables. The relationships between some of the variables are found to be statistically significant with p-values close to 0. Detailed regression analysis results can be found in Appendix H. In general, we find that

- when the wholesale price increases, the buyback price also increases
- when the buyback price increases, stock quantity ordered by the retailer increases
- when the difference between the wholesale price and the buyback price increases, stock quantity ordered by the retailer decreases
- when the wholesale price increases, stock quantity ordered by the retailer decreases
- when stock quantity ordered by the retailer increases, the manufacturer's profit increases.

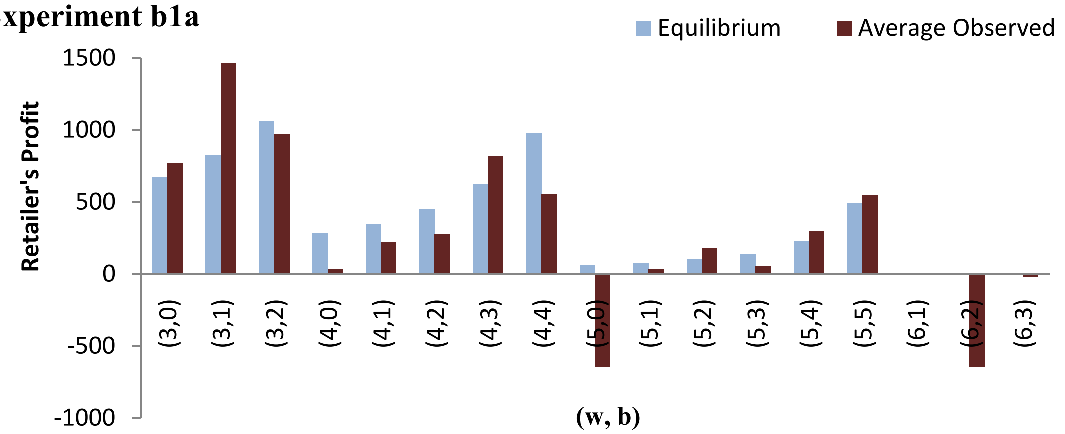
Note that there is nothing surprising about these relationships. They are all intuitive, and these results serve as a logical check of our overall data.

For a given wholesale price, the model predicts that, when buyback price increases, both the manufacturer's and the retailer's profit increases, primarily because the retailers order more. As presented in Figure 5.19, we analyzed the manufacturer's and the retailer's average observed profit for each selected $(w, b)$ couple in w & b setting experiments and compared these values with the theoretical predictions. We observe that the change in the profits is consistent with the model's predictions. For a given wholesale price, when buyback price increases, both the manufacturer's and the retailer's average observed profit increases.

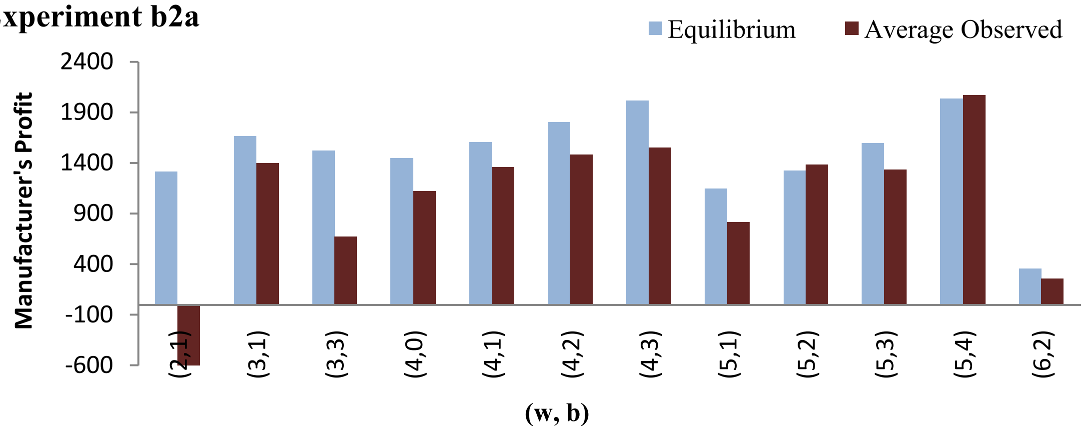
Experiment b1a



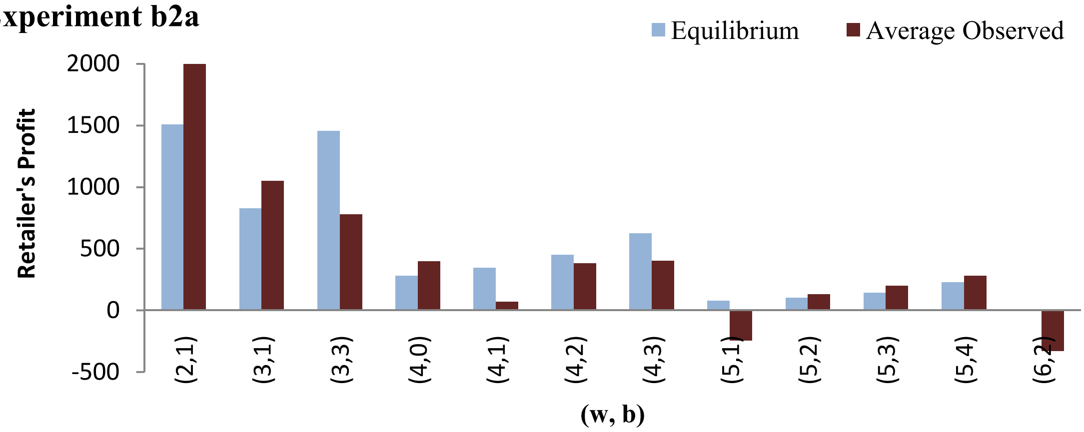

Experiment b1a




Experiment b2a




Experiment b2a



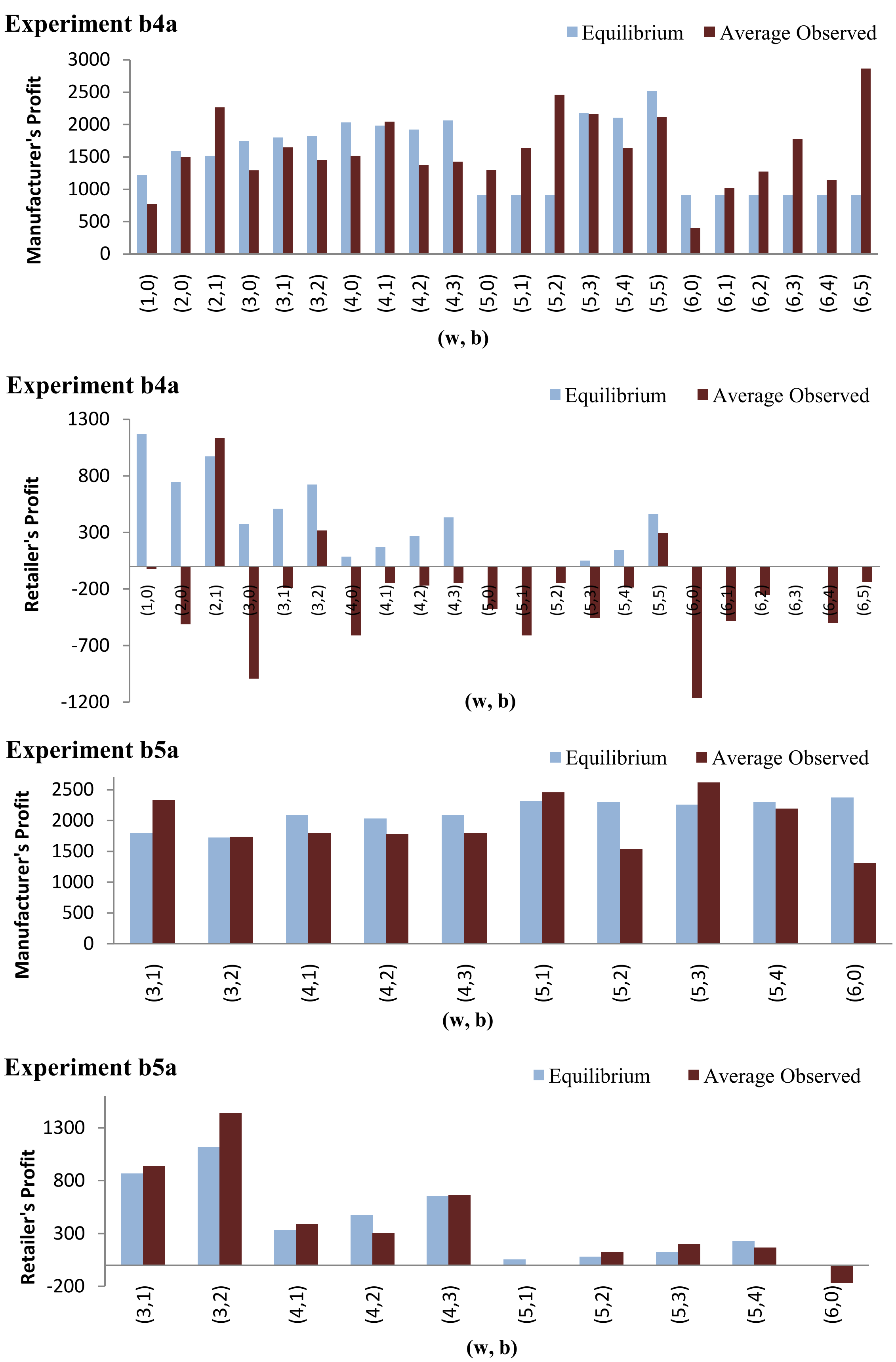



Figure 5.19. Manufacturer's and Retailer's Profit for (w, b) in w & b Setting Experiments

In Figure 5.19, we observed an interesting phenomenon: The manufacturer's average observed profit is higher than the equilibrium profit for some $(w, b)$ couples (such as couples (5,0), (5,1), (5,2), (6,2) and (6,3) in experiment b1a, and (2,1), (5,0), (5,1), (5,2), (6,1), (6,2), (6,3), (6,4) and (6,5) in experiment 4a). For these cases, we found that the average observed stock level is higher than the equilibrium. As the retailers ordered more, the manufacturers made more profit than predicted. Average stock levels ordered by retailers in experiment b1 and b4a are shown in Figure 5.20.

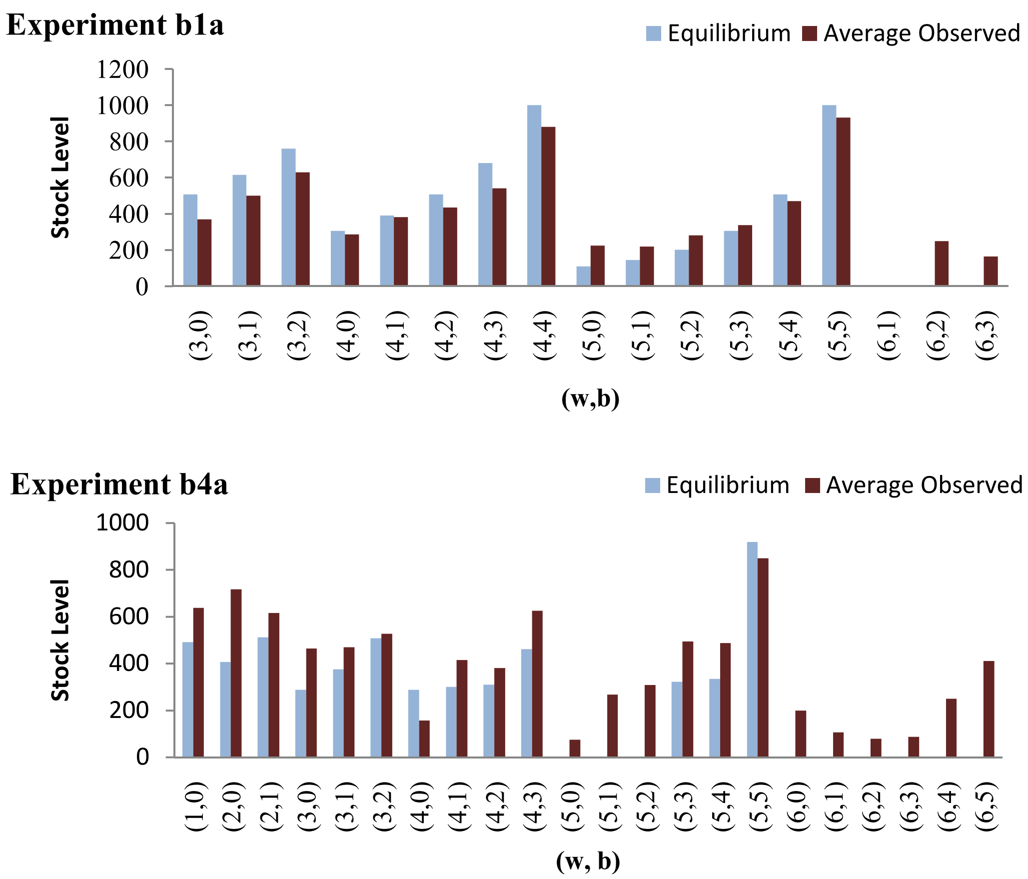



Figure 5.20. Average Stock Levels for (w, b) in Experiments b1a and b4a

Next, we focus on the effect of buyback price on the firms' profits. Below in Figure 5.21, we compare the manufacturer's average observed and theoretical prediction profits for the optimal wholesale price values (set-w in experiments b1a, b2a, b4a and b5a, and given-w in experiments b3a and b6a). The optimal buyback price is marked with an asterix[10]. From the figure, it is clear that the manufacturer's average observed profit increases when the buyback price increases.

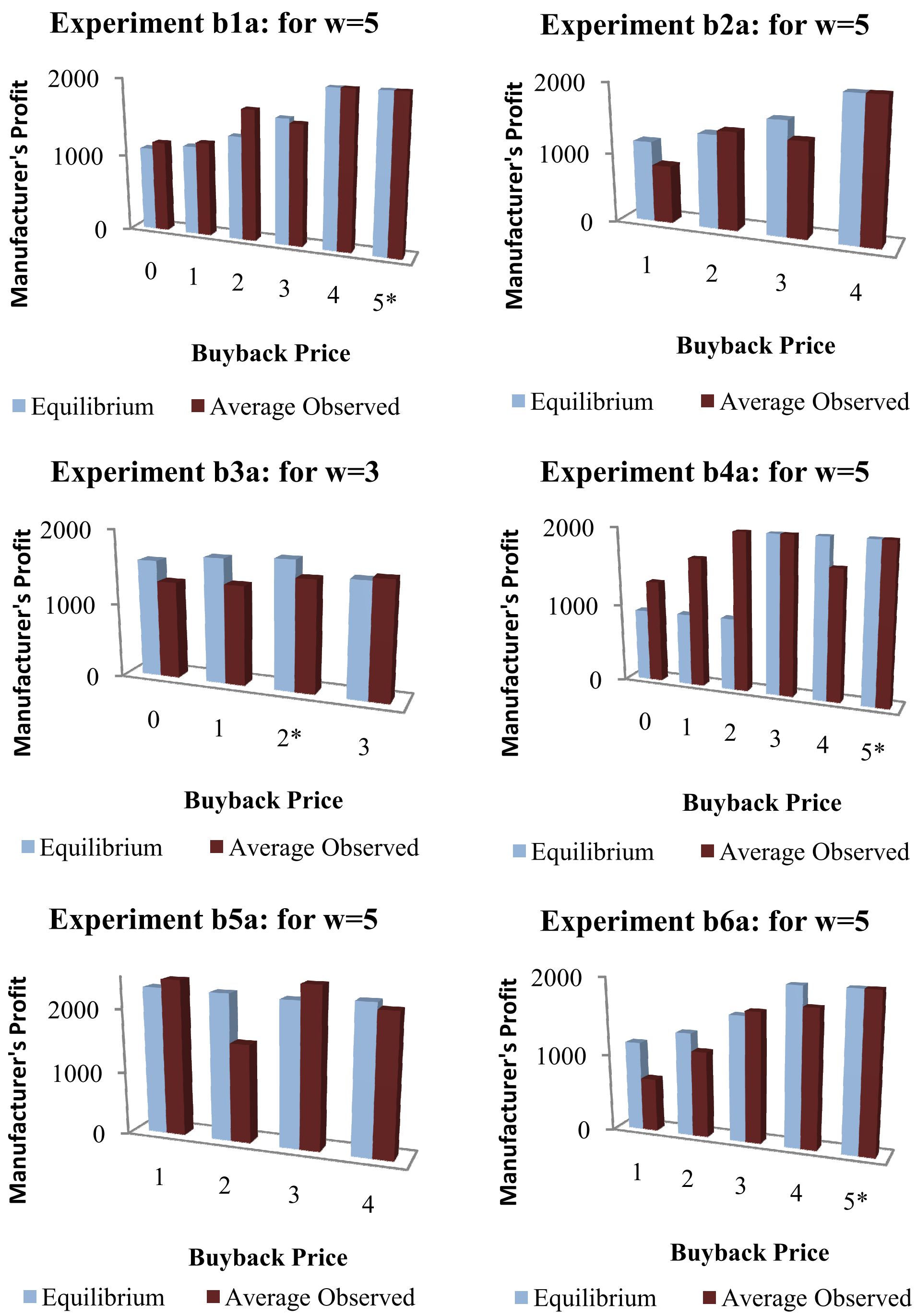



Figure 5.21. Manufacturer's Profit as a Function of the Buyback Price for the Optimal Wholesale Price

[10] In some of the cases, we could not mark the optimal buyback price. Since this buyback price is not selected by the decision-makers. Thus, there exists no observed data for them.

# CHAPTER 6

## CHAPTER 6 : COMPARISON OF WHOLESALE PRICE AND BUYBACK CONTRACT EXPERIMENTS

In this chapter, we compare the wholesale price contract experiments (WPCE) with buyback contract experiments (BCE), to find out whether our theoretical predictions for different contract settings hold.

According to Gökduman and Kaya (2009), buyback contract outperforms the wholesale price contract in terms of manufacturer's profit and total system profit. Thus, we expect that our BCE results will be better than WPCE results in terms of profits. In order to understand which contract type performs better in experiments, we compare the wholesale price contract w-setting experiments with buyback contract w & b setting experiments for each given parameter set $(p, c, k, m, v)$, and wholesale price contract given-w experiments with buyback contract given-w & b-setting experiments for each given parameter set $(p, c, k, m, v)$ and wholesale price $w$.

### 6.1. Comparison of w-Setting Experiments with w & b Setting Experiments

Table 6.1. Parameter Sets of Experiments in w-Setting and w & b Setting Type

| Parameter Set | $k$ | $m$ | $v$ | $p$ | Exp. | Exp. Type |
|---|---|---|---|---|---|---|
| 1 | 2 | 100,000 | 10 | 6 | 4a | w-setting |
| | | | | | 5a | w-setting |
| | | | | | b1a | w & b setting |
| | | | | | b2a | w & b setting |
| 2 | 8 | 200,000 | 15 | 6 | 6a | w-setting |
| | | | | | b4a | w & b setting |
| 3 | 0 | 10,000 | 10 | 6 | 7a | w-setting |
| | | | | | b5a | w & b setting |

In total, we have three different parameter sets $(p, c, k, m, v)$ for the experiments, which are in w-setting type in WPCE, and w & b setting type in BCE. These experiments are shown in Table 6.1.

We compared manufacturer's profit, retailer's profit and total system profit of the experiments in each parameter set by illustrating the average observed and theoretical equilibrium values.

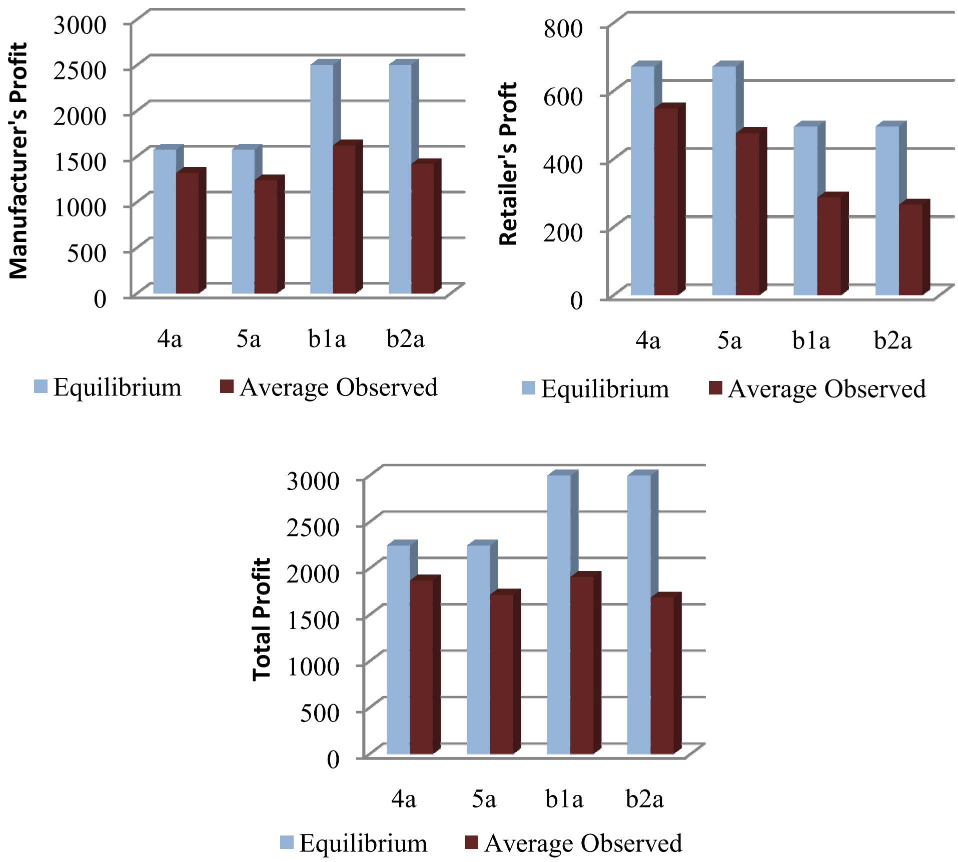



Figure 6.1. Comparison of w-Setting and w & b Setting Experiments for Parameter Set I

For parameter set I, comparison of profits are shown in Figure 6.1. Manufacturer's average observed profit is higher on average in both of the BCE (i.e., experiments b1a, b2a) in comparison to the WPCE (i.e., experiments 4a, 5a). However, the manufacturer's average observed profit is not as high as predicted by the equilibrium in BCE. The retailer's average observed profit is lower in BCE (i.e., b1a, b2a) in comparison to WPCE (i.e., 4a, 5a) as predicted by the model. However, the retailer's average observed profit is much more lower than theoretical predictions in BCE. We observe that the average $(w, b)$ values are lower in the experiment b2a than in b1a. In addition, the average observed buyback price in experiment b2a is lower than that in experiment b1a for each given wholesale price (i.e., except in the case of $w = 3$, which has a very low choice frequency in experiment b2a). Thus, in experiment b2a, the retailers set their stocking quantities much more lower than expected, and get lower profit. Average observed total system profit in BCE is higher than WPCE only in experiment b1a.

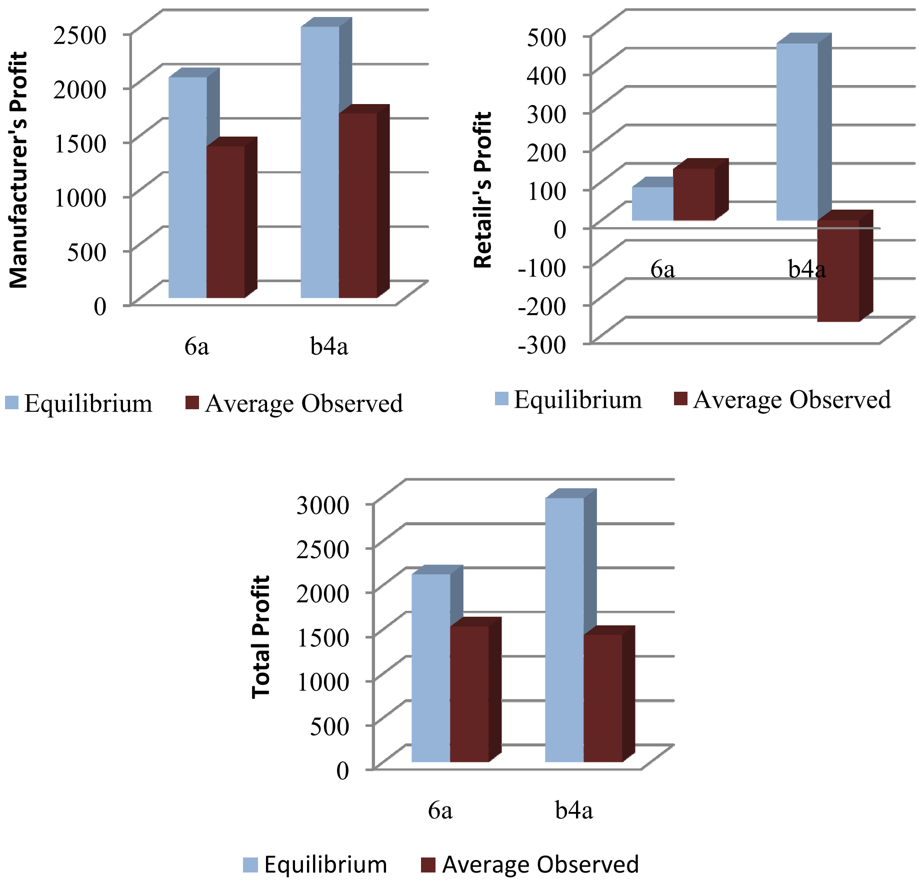



Figure 6.2. Comparison of w-Setting and w & b Setting Experiments for Parameter Set II

For parameter set II, comparison of profits are shown in Figure 6.2. Manufacturer's observed profit increased on average when the contract type changes from wholesale price (i.e., experiment 6a) to buyback (i.e., experiment b4a); however, retailer's observed profit and observed total system profit decreased on average. The average observed wholesale price is 4.55, and buyback price is 1.78, which is much below the theoretical optimal value of 5. Given a relatively high $w$ and relatively low $b$, the retailers should have ordered low quantities, even zero units. However, they kept ordering more than that, and this caused them to obtain negative profits on average. Compared to WPCE, the retailer's average observed profit and average observed total system profit are less in BCE because of this over-ordering.

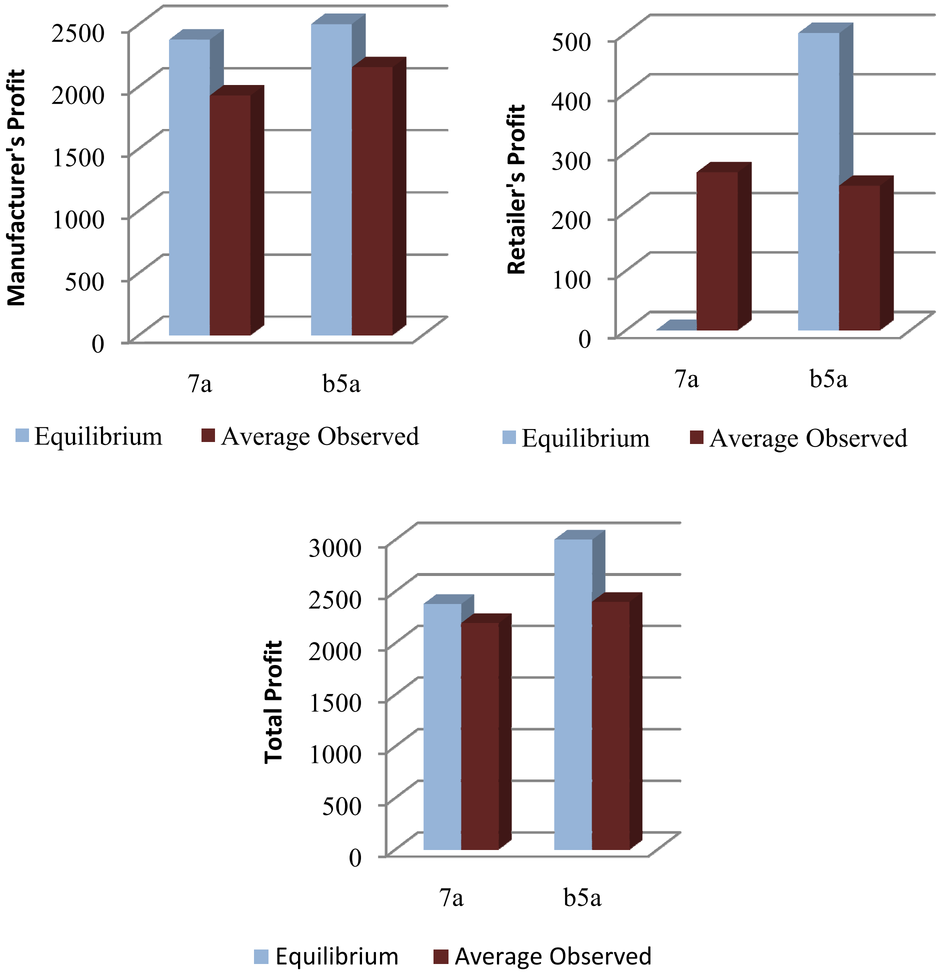



Figure 6.3. Comparison of w-Setting and w & b Setting Experiments for Parameter Set III

For parameter set III, comparison of profits are shown in Figure 6.3. Both manufacturer's observed profit and observed total system profit are increased on average when the contract type changes from wholesale price (i.e., experiment 7a) to buyback (i.e., experiment b5a). However, retailer's average observed profit is decreased which should have increased according to theoretical predictions. Retailers ordered more on average in BCE in comparison to WPCE; but, they did not order as much as the theoretical prediction.

## 6.2. Comparison of Given-w Experiments with Given-w & b-Setting Experiments

We have one parameter set $(p, c, k, m, v)$ for the experiments, which are in given-w type in wholesale price contract experiments, and given-w & b-setting type in buyback contract experiments. The experiments in this parameter set are shown in Table 6.2.

Table 6.2. Parameter Set of Experiments in Given-w and Given-w & b-Setting Type

| **Parameter set** | $\boldsymbol{k}$ | $\boldsymbol{m}$ | $\boldsymbol{v}$ | $\boldsymbol{p}$ | $\boldsymbol{w}$ | **Exp.** | **Exp. Type** |
|---|---|---|---|---|---|---|---|
| 4 | 2 | 100,000 | 10 | 6 | 3 | 4b | given-w |
| | | | | | | 5b | given-w |
| | | | | | | b3a | given-w & b-setting |

We compared manufacturer's profit, retailer's profit and total system profit of the experiments by illustrating average observed and theoretical equilibrium values.

For parameter set IV, comparison of profits is shown in Figure 6.4. Manufacturer's observed profit, retailer's observed profit and observed total system profit are increased on average when the contract type changes from wholesale price (i.e., experiments 4b and 5b) to buyback (i.e., experiment b3a). In all of these experiments, the wholesale price is given as 3. This wholesale price is relatively lower in comparison to the average wholesale price set in the experiments b1a and b2a, which are w & b setting version of the same experiment. Because the average observed buyback price set in experiment b3a is 1.74, which is close to theoretical optimal value of 2, retailer's average observed stock level is close to equilibrium prediction. As a result, all supply chain members profited from the buyback contract in comparison to the wholesale price contract.

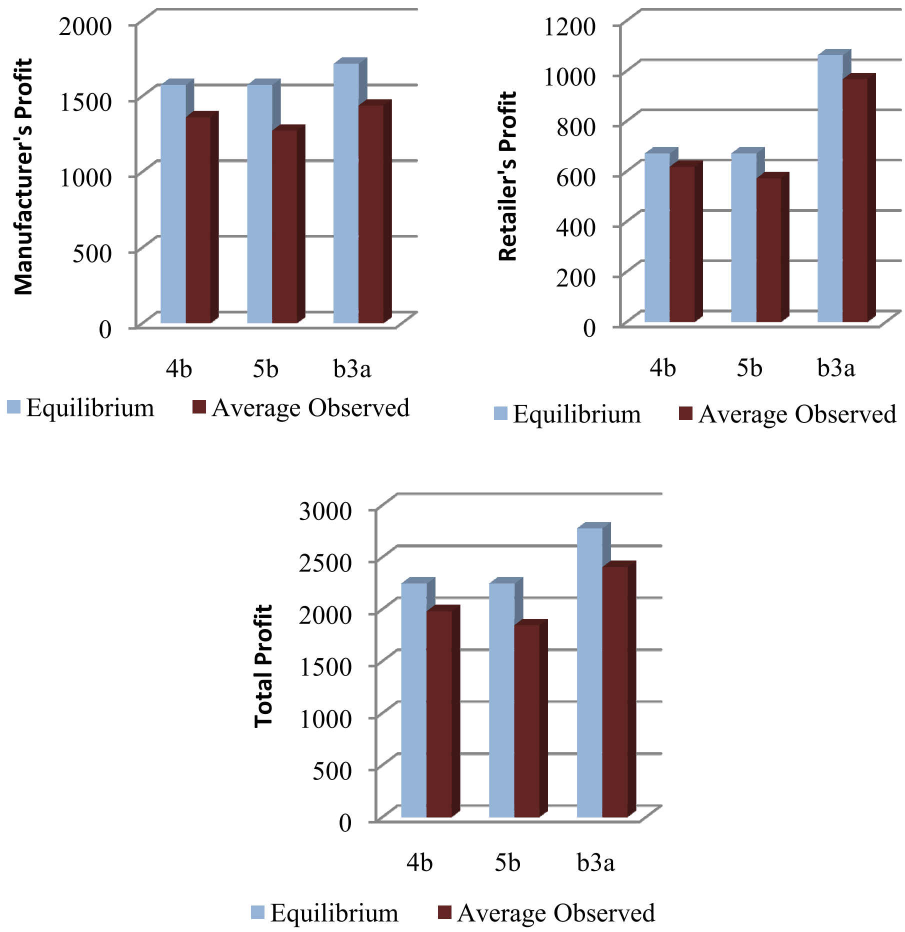



Figure 6.4. Comparison of Given-w and Given-w & b-Setting Experiments for Parameter Set IV

In conclusion, for the same parameter set, manufacturer's average observed profit increases when the contract changes from wholesale price into buyback. However, manufacturer’s average observed profit do not increase as much as predicted, because manufacturers usually select an aggressive $(w, b)$ set which is very profitable for them, but not profitable for the total system and retailers. As a result, although the retailers order more in BCE compared to WPCE, their average observed profit is less than predicted by the model and their average observed profit in the WPCE. This affects the average total system profit. In general, the total system does not profit as much as expected on average, in some cases, even less than the average observed total system profit in WPCE. The buyback contract outperforms the wholesale price contract in terms of total system efficiency, but the profits are not as high as expected by the theoretical model.

# CHAPTER 7

## CHAPTER 7 : ANALYSIS OF THE FACTORS AFFECTING DECISIONS

Although the periods of an experiment in our experimental study are independent (i.e., a outcome in a period is not affected directly from any decision in a previous period), the decision in a given period might be affected by the outcome of the previous period due to behavioral reasons. For example, a subject that incurred a loss in a given period might make a more cautious decision in the next period. Given the complexity of our experiment setting (two decision stages, random total demand etc.), it is not easy to pinpoint the exact behavioral factors (loss aversion, irrationality, decision heuristics etc.) that affect participants' decisions. At least, however, we can check whether the subjects' decisions in a given period can be explained by a multiple regression model using variables related to previous period's decisions and outcomes. Constructing such models would give us clues about the underlying behavioral factors that affect decisions.

Here, we analyze the factors affecting the stock level decisions of retailers and delivery lead time decisions of manufacturers in the WPCE[11]. We used simple and multiple linear regression, and autocorrelation analysis. For a brief explanation on the multiple linear regression, please see the Appendix I.

### 7.1. Retailer's Stock Level Decision

Here, we analyze retailer subjects' stock level decisions in order to find the behavioral reasons underlying their decisions. First, we control whether there is a significant relationship between the stock level decision and other variables. We control the relationship with multiple and simple regression analysis for each experiment and each subject. Second, we control whether there is a significant relationship of each subject's

[11] Analysis regarding to BCE can be obtained from the authors.

stock level decision at a period with his decisions at the previous periods. To do this, we make an autocorrelation analysis.

### 7.1.1. Multiple Linear Regression Analysis

For analyzing the relationship between the retailer's stock level decision and the other variables (i.e., if the decision of the retailer is affected by the changes in other variables), and measuring the effect of each variable on the retailer's stock level decision, we used multiple linear regression as the method and SPSS as the statistical tool.

We chose "backward" as the variable selection method and conducted all of our regression analysis using this method in SPSS. As we have many candidate predictor variables and data of many subjects who behave differently, we did not use simultaneous selection methods (i.e., "enter" or "remove"). The "stepwise" did not succeed in many of our regression analysis, because it aims to provide the least number of predictor variables in the model. In addition, the "forward" selection method showed similar results with "stepwise" and the results were not available for some cases. As such, we decided to use the "backward" method.

We worked on all experiments and conducted regression analysis to regress "the retailer's stock level decision at period t" with 7 different predictor variables. These variables and their abbreviations used in the regression result tables are shown in Table 7.1. We tested the null hypothesis that there is no relationship between retailer's stock level decision and the variables stated in the table.

Table 7.1. Predictor Variables for Multiple Linear Regression Analysis of Retailer's Stock Level Decision

| Variable | Abbreviation |
|---|---|
| retailer's sale at period t-1 | saler |
| retailer's profit at period t-1 | profitr |
| retailer's stock level decision at period t-1 | stock |
| total demand at period t-1 | demandt |
| retailer's overage at period t-1 | overage |
| lost-retailer demand at period t-1 | lostrd |
| wholesale price at period t | wprice |

The predictor variable “wholesale price at period t” is only considered for the w-setting experiments. The variable “retailer’s overage” denotes the retailer’s excess inventory when excess inventory exists, and the retailer’s lost demand quantity when the retailer loses demand.

In addition to stated predictor variables in the table, we had selected “unsold retailer stock at period t-1” and “retailer demand at period t-1” as the other candidates for predictor variables. However, the analysis that included these variables did not result in significant regression equations for some of the cases. This was due to high multi-collinearity between the predictor variables. First, there is a strong correlation between overage and unsold retailer stock. In some analyses, the correlation coefficient between these variables is equal to 1. The simple linear regression of unsold retailer stock and stock level indicated a very weak relationship. Hence, we removed this variable from our analysis. Second, retailer demand is stochastic and it did not exist in any final regression equation we obtained. It has a correlation with retailer's sale, retailer's profit and total demand. In addition, retailer demand is a fraction of total demand. Thus, we removed this variable from our analysis as well.

The analysis is conducted for two different data: experiment-based (where all subjects’ data is collected together to see the general trend) and subject-based (to investigate subject-based decisions). In subject-based investigations, we analyzed each experiment data for each subjects’ decisions separately.

Experiments that include at least 70% of the time the same stock level decision were excluded from the experiment-based analysis. Similarly, subjects who chose at least 70% of the time the same stock level in a given experiment were excluded from the subject-based analysis. For such experiments or subjects, $R^2$ values might be artificially high; however, these $R^2$ values do not convey meaningful information. These are stated as “Discarded” in the regression result tables.

For all of the variables stated in the regression result tables, the VIF statistic is less than 10. We discarded the variables with a VIF more than 10 to avoid the effect of multi-collinearity.

#### 7.1.1.1. Experiment-based Analysis

Experiment-based regression analysis resulted with significant regression equations for all of the experiments. However, the $R^2$ values are found to be less than 0.5 for most cases.

Experiment-based regression analysis results are shown below in Table 7.2. The column “Ses.” presents the session and “Exp.” presents the experiment. If the stock level decision is expressed by an equation of at least one predictor variable being significant (i.e., if the regression model passed the F test and p-value $\leq$ 0.1), the “response” for that experiment is defined as “yes”. “Response variables” show which predictor variables are in the regression model. We also provide the $R^2$, adjusted $R^2$ and F-test p-values. “Equation” shows the regression model of the significant analysis, where p-value is less than 0.1. Absolute regression coefficient (absolute beta values) of each predictor variable in an equation indicates the power of that variable in predicting the stock level decision.

The analysis shows that the set of factors that affect the decisions depend on the experiment. However, previous period stock level is a significant variable that affects the stock level decision in most of the experiments. Wholesale price in the current period is also a significant variable in all of the w-setting experiments as indicated by its high absolute beta value.

Experiment-based results give an idea about how most of the subjects behaved in a given experimental setup. However, as the $R^2$ values are not large enough, we may not say that the equations are successful in predicting the behavior of all subjects. In experiment 7a, the $R^2$ value is high due to the impact of the wholesale price on the retailer’s quantity decision. The significance is 0 for all of the regression equations, indicating that the models strongly (i.e., without error) reject the null hypothesis that there is no relationship between the stock level decision and the stated response variables.

Table 7.2. Experiment-based Multiple Regression Analysis of Stock Level Decision

| Ses. | Exp. | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1 | 1a | yes | overage, stock, lostrd | 0.163 | 0.144 | 0.000 | stock = 227.741 + 0.447*stock - 0.302*lostrd - 0.246*overage |
| | 1b | yes | stock | 0.309 | 0.302 | 0.000 | stock = 93.638 + 0.572*stock |
| | 1c | Discarded | | | | | |
| 2 | 2a | yes | demandt, overage | 0.150 | 0.137 | 0.000 | stock = 204.512 + 0.325*demandt + 0.412*overage |
| | 2b | yes | stock, demandt, overage | 0.442 | 0.426 | 0.000 | stock = 127.221 + 0.692*stock - 0.087*demandt - 0.145*overage |
| | 2c | Discarded | | | | | |
| 3 | 3a | yes | stock, demandt, overage | 0.473 | 0.455 | 0.000 | stock = 32.037 + 0.375*stock + 0.465*demandt + 0.417*overage |
| | 3b | yes | overage, saler | 0.204 | 0.188 | 0.000 | stock = 224.629 + 0.510*saler + 0.218*overage |
| | 3c | yes | saler, overage | 0.585 | 0.575 | 0.000 | stock = 17.435 + 1.002*saler + 0.410*overage |
| 4 | 4a | yes | wprice, profitr, saler | 0.321 | 0.312 | 0.000 | stock = 547.886 + 0.535*saler - 0.077*profitr - 91.873*wprice |
| | 4b | yes | stock, saler | 0.303 | 0.296 | 0.000 | stock = 194.884 + 0.608*stock - 0.148*saler |
| 5 | 5a | yes | stock, wprice | 0.270 | 0.258 | 0.000 | stock = 567.070 + 0.245*stock - 99.494*wprice |
| | 5b | yes | stock, profitr | 0.359 | 0.346 | 0.000 | stock = 171.889 + 0.571*stock - 0.040*profitr |
| 6 | 6a | yes | stock, profitr, wprice | 0.331 | 0.320 | 0.000 | stock = 540.204 + 0.315*stock - 0.029*profitr - 115.698*wprice |
| | 6b | yes | saler, overega | 0.402 | 0.391 | 0.000 | stock = 53.883 + 0.805*saler + 0.309*overage |
| 7 | 7a | yes | stock, wprice | 0.539 | 0.534 | 0.000 | stock = 787.303 + 0.230*stock - 136.222*wprice |
| | 7b | Discarded | | | | | |

#### 7.1.1.2. Subject-based Analysis

The regression analysis results of the subject-based experiments are provided in Appendix J. Here we provide a summary of our observations. The subject-based regression analysis shows different results depending on the subject and the experiment. The most important observation is that we cannot talk of a set of significant variables that affect most subjects' stocking level decision consistently, in general. The only exception is the wholesale price in the w-setting experiments (i.e., 4a, 5a, 6a, 7a). However, there are variables, which are responded by all subjects in a given experiment. For example, all subjects responded to retailer's sale in experiment 2c and overage in experiment 3a.

We obtained some more specific observations from the subject-based analysis. First, we can trust on the models in predicting the subjects' behaviors. This fact is due to high prediction power (i.e., the $R^2$ values are greater than 0.5), and low significance of the models (i.e., the p-vales are less than 0.05) for most of the cases.

Second, response of subjects to our predictor variables depends on the subjects, the experimental environment (the parameter set) and the type of the experiment. An example of subjects' differing behavior in the same experiment can be observed in experiment 1a in which there are some subjects whose response to a particular variable is positive and other subjects whose response is negative. An example for subjects being sensitive to experimental environment is subject 8 in session 1. He did not respond to any variable in experiment 1a; however, he responded to some variables in experiments 1b and 1c. This observation is the behavior of many subjects in sessions 1, 2 and 3. As examples for the effect of experiment type, we provide the situation in sessions 6 and 7. In experiments 6a and 7a, all subjects responded to at least one variable; whereas, in experiments 6b and 7b none of the subjects responded to any variable while deciding on the stock level. This is because experiments 6a and 7a are w-setting experiments; while, experiments 6b and 7b are given-w experiments.

Third observation is about w-setting experiments (i.e., 4a, 5a, 6a and 7a). In these experiments, all subjects responded to the wholesale price except subject 7 in experiment 4a. In all of these cases, the wholesale price is the most powerful predictor of the stock level decision and it negatively affects the stock level. This is not surprising because the wholesale price is related to the same period, and hence, directly affects the profit structure of the retailer, whereas the other predictor variables are related to the previous period.

We also detected groups of subjects who respond to the same variables in a given experiment. For example, in experiment 4b, subjects 2, 10 and 12 only responded to total demand, in experiment 6a, subjects 4 and 5 only respond to the wholesale price while subjects 8 and 9 respond to both lost retailer demand and wholesale price. In experiment 7a, subjects 0, 3, 4, 6, 7, 8 and 9 only respond to the wholesale price. However, none of the subjects responded to only the same set of variables in different experiments of a session.

### 7.1.2. Multiple Linear Regression Analysis with Dummy Variables

We wanted to deepen our analysis related to the relationship between retailer's stock level decision and predictor variables stated before. To this end, instead of using the numerical values of some variables directly, we used 1/0 dummy variables where 1 indicates presence of a characteristic and 0 indicates its absence.

We changed three of our predictor variables into dummy variables. These variables are "retailer's sale at period t-1", "retailer's profit at period t-1", and "lost-retailer demand at period t-1". Below in Table 7.3, we provide the "characteristic" that we searched in each variable values, our "logical test" to categorize the values, and new "categorical values" related to each logical test.

Table 7.3. Dummy Variables

| **Variable** | **Characteristic** | **Logical Test** | **Categorical Value** |
|---|---|---|---|
| retailer's sale at period t-1 | Positive retailer's sale | retailer's sale > 0 | 1 |
| | | retailer's sale <= 0 | 0 |
| retailer's profit at period t-1 | Positive retailer's profit | retailer's profit > 0 | 1 |
| | | retailer's profit <= 0 | 0 |
| lost-retailer demand at period t-1 | No lost-retailer demand | lost-retailer demand = 0 | 1 |
| | | lost-retailer demand ≠ 0 | 0 |

As an example, the values of the variable “retailer’s sale at period t-1” are changed according to the characteristic “positive retailer’s sale”. If the retailer’s sale at a period is greater than 0, its value is replaced with“1”. If the retailer’s sale at a period is less than or equal to 0, its value is replaced with “0”.

We conducted another multiple regression analysis to investigate the factors affecting stock level decision with the predictor variables presented in Table 7.4. We tested the null hypothesis that there is no relationship between retailer’s stock level decision and the variables stated in the table.

Table 7.4. Predictor Variables for Multiple Linear Regression Analysis of Stock Level Decision with Dummy Variables

| Variable | Type |
|---|---|
| stock level at period t-1 | continuous |
| total demand at period t-1 | continuous |
| retailer's sale at period t-1 | dummy |
| retailer's profit at period t-1 | dummy |
| lost-retailer demand at period t-1 | dummy |
| overage at period t-1 | continuous |
| wholesale price at period t | continuous |

We refer to the analysis with dummy variables as the “new” analysis, and the previous one without dummy variables as the “previous” analysis. For all of the variables in the regression result tables, the VIF statistic is less than 10 to avoid the effect of multi-collinearity.

#### 7.1.2.1. Experiment-based Analysis

Table 7.5 below summarizes the results of our experiment-based regression analysis with dummy variables.

New analysis results support the major conclusions derived from the previous analysis. The set of factors that affect the decisions depend on the experiment, previous period stock level is a significant variable, and wholesale price in the current period is a significant variable in all of the w-setting experiments. New analysis improved the $R^2$

and adjusted $R^2$ values for most of the experiments. In most of the regression equations, the significant variables are changed in comparison to the previous analysis.

Table 7.5. Experiment-based Multiple Regression Analysis of Stock Level Decision with Dummy Variables

| Ses. | Exp. | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1 | 1a | yes | stock, lostrd, overage | 0.166 | 0.148 | 0.000 | stock = 173.698 + 0.422*stock + 70.064*lostrd - 0.239*overage |
| | 1b | yes | profitr, lostrd, overage | 0.362 | 0.344 | 0.000 | stock = 334.963 + 125.248*profitr - 244.196*lostrd + 0.676*overage |
| | 1c | Discarded | | | | | |
| 2 | 2a | yes | stock, saler | 0.211 | 0.199 | 0.000 | stock = 593.427 + 0.387*stock - 364.461*saler |
| | 2b | yes | stock, demandt, lostrd | 0.443 | 0.428 | 0.000 | stock = 185.790 + 0.604*stock - 0.086*demandt - 62.468*lostrd |
| | 2c | Discarded | | | | | |
| 3 | 3a | yes | stock, demandt, saler | 0.464 | 0.446 | 0.000 | stock = 232.777 + 0.953*stock + 0.159*demandt - 310.924*saler |
| | 3b | yes | stock, profitr | 0.199 | 0.184 | 0.000 | stock = 203.755 + 0.349*stock + 53.887*profitr |
| | 3c | yes | stock, overage | 0.589 | 0.580 | 0.000 | stock = 14.212 + 0.862*stock - 0.386*overage |
| 4 | 4a | yes | wprice, stock | 0.308 | 0.301 | 0.000 | stock = 554.654 - 90.538*wprice + 0.254*prestock |
| | 4b | yes | stock, profitr | 0.299 | 0.291 | 0.000 | stock = 222.963 + 0.508*stock - 41.591*profitr |
| 5 | 5a | yes | wprice, stock, saler, lostrd, overage | 0.323 | 0.295 | 0.000 | stock = 716.373 - 101.214*wprice + 0.255*stock - 116.962*saler - 60.265*lostrd + 0.083*overage |
| | 5b | yes | stock, demandt | 0.332 | 0.319 | 0.000 | stock = 191.557 + 0.567*stock - 0.083*demandt |
| 6 | 6a | yes | stock, wprice | 0.318 | 0.310 | 0.000 | stock = 525.246 + 0.311*stock - 111.471*wprice |
| | 6b | yes | stock, profitr | 0.418 | 0.407 | 0.000 | stock = 50.094 + 0.450*stock + 124.162*profitr |
| 7 | 7a | yes | wprice, stock | 0.539 | 0.534 | 0.000 | stock = 787.303 - 136.222*wprice + 0.230*stock |
| | 7b | Discarded | | | | | |

#### 7.1.2.2. Subject-based Analysis

Results of the subject-based multiple regression analysis of the experiments with dummy variables are presented in Appendix K. This new analysis indicates different results depending on the subject, the experimental environment (the parameter set) and the type of experiment as in the previous analysis. The most important observation is that we can still not talk of a set of significant variables that affect most subjects' stocking level decision, in general. The only exception is the wholesale price in the w-setting experiments (i.e., 4a, 5a, 6a, 7a).

Our more specific observations related to new analysis consist of several points. First, the new analysis increased the number of positive response in total. There are 10 new cases, in which a regression model explains the stock level decision significantly (passed the F test and p-value is less than 0.1). However, we observed 6 reverse cases, in which the stock level decisions are expressed by a regression equation significantly in the previous analysis, but not expressed significantly in the new analysis. One reason for this situation, which is observed for subject 6 in experiment 1a, and subjects 6 and 11 in experiment 4b, is that the response variable that is obtained in the previous analysis could not be included in the new analysis because all values of the predictor variable turned out to be 1 or 0 for some of the subjects. Another reason is that some predictor variables turned out to be insignificant in explaining the stock level decision because changing the variable type caused to lose information. This is observed for subject 4 in experiment 3b, subject 6 in experiment 3c, and subject 7 in experiment 4a.

Second, new subject-based analysis did not result in improved $R^2$, Adj. $R^2$ and p-values for all cases. There are some cases in which these values are deteriorated, and some others in which these values stayed the same. As a result, we can say that an improvement in $R^2$, Adj. $R^2$ and significance values is not observed in general.

### 7.1.3. Simple Linear Regression Analysis

We also conducted simple linear regression analyses between the stock level decision and each predictor variable alone. We tested the null hypothesis that there is no relationship between the stock level decision and the predictor variable. As an example, we provide the analysis on subject 9 in experiment 1a. We knew from the multiple linear regression analysis that subject 9 responded to three predictor variables in experiment 1a resulting with a multiple regression equation of stock(t) = 512.679 + 0.947*retailer's sale(t-1) - 0.534*total demand(t-1) - 0.635*overage(t-1) with an $R^2$ of 0.717 and p-value of 0.008. Related regression data is provided below in Table 7.6.

Table 7.6. Subject 9's Regression Data in Experiment 1a

| Stock Level (t-1) | Total Demand (t-1) | Retailer's Sale (t-1) | Retailer's Profit (t-1) | Lost-Retailer Demand (t-1) | Overage (t-1) | Stock Level (t) |
|---|---|---|---|---|---|---|
| 500 | 896 | 500 | 3000 | 97 | -97 | 600 |
| 600 | 567 | 435 | 1950 | 297 | -297 | 600 |
| 600 | 682 | 565 | 3250 | 170 | -170 | 600 |
| 600 | 362 | 291 | 510 | 251 | -251 | 500 |
| 500 | 546 | 413 | 2130 | 179 | -179 | 450 |
| 450 | 115 | 83 | -970 | 0 | 196 | 200 |
| 200 | 295 | 182 | 1020 | 299 | -299 | 450 |
| 450 | 102 | 85 | -950 | 0 | 95 | 500 |
| 500 | 123 | 99 | -1010 | 0 | 75 | 200 |
| 200 | 281 | 178 | 980 | 0 | 155 | 600 |
| 600 | 43 | 34 | -2060 | 462 | -462 | 100 |
| 100 | 875 | 100 | 600 | 318 | -318 | 300 |
| 300 | 796 | 300 | 1800 | 0 | 109 | 500 |

Below in figures, the relationship between each predictor variable and subject 9's stock level decision are plotted. The regression equations, $R^2$ values and p-values are also provided.

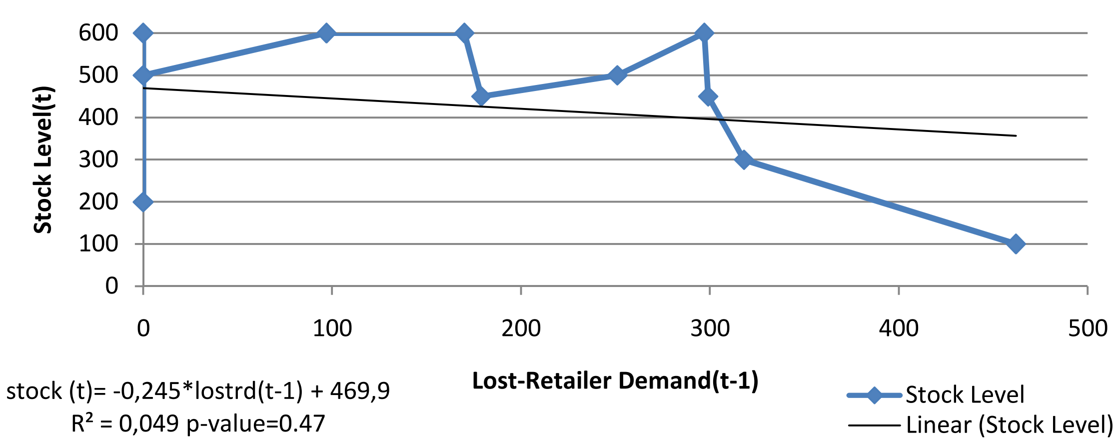



Figure 7.1. Retailer's Stock Level(t) vs. Lost-Retailer Demand(t-1) in Exp. 1a

Figure 7.1 shows that subject 9's stock level decision at period t and his lost demand at period t-1 are negatively related. The absolute beta value shows that a change in the lost-retailer demand affects his decision moderately. However, proportion of the variance in stock level explained by the model (i.e., the $R^2$ value) is very small and p-value is greater than 0.1, thus we cannot reject the null hypothesis that there is no relationship between stock level decision and previous period lost-retailer demand. Note that the existence of "zero" predictor values (i.e., when there is no lost-retailer demand) deteriorate the quality of the regression.

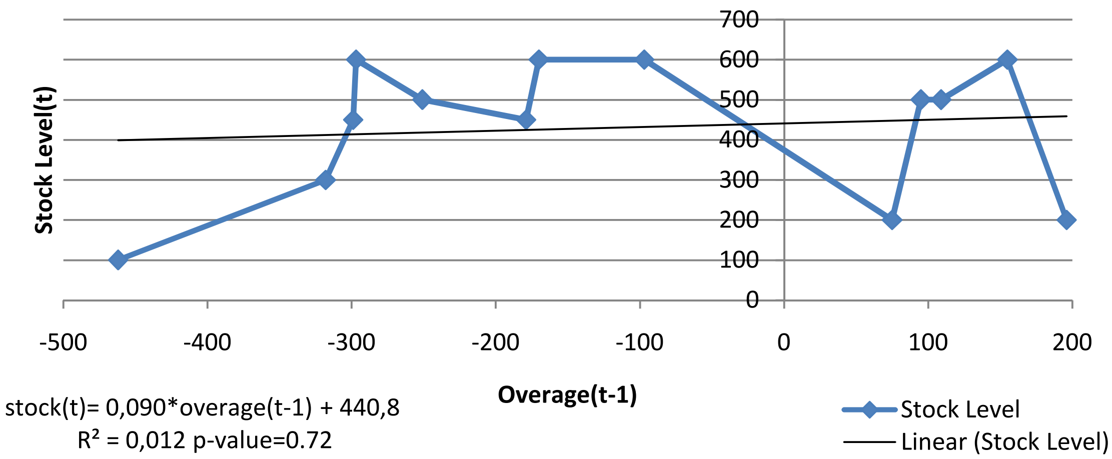



Figure 7.2. Retailer's Stock Level(t) vs. Overage(t-1) in Exp. 1a

Figure 7.2 shows that subject 9's stock level decision at period t and his "overage at period t-1" are positively related. However, the beta value of the overage is only 0.090 which shows that a change in overage has a very small effect on the subject 9's decision. $R^2$ value is 0.012, which shows that the model's success in explaining the variance of the stock level is very low. P-value is greater than 0.1, so we say that there is not enough evidence to reject the null hypothesis that there is no relationship between overage in previous period and stock level decision.

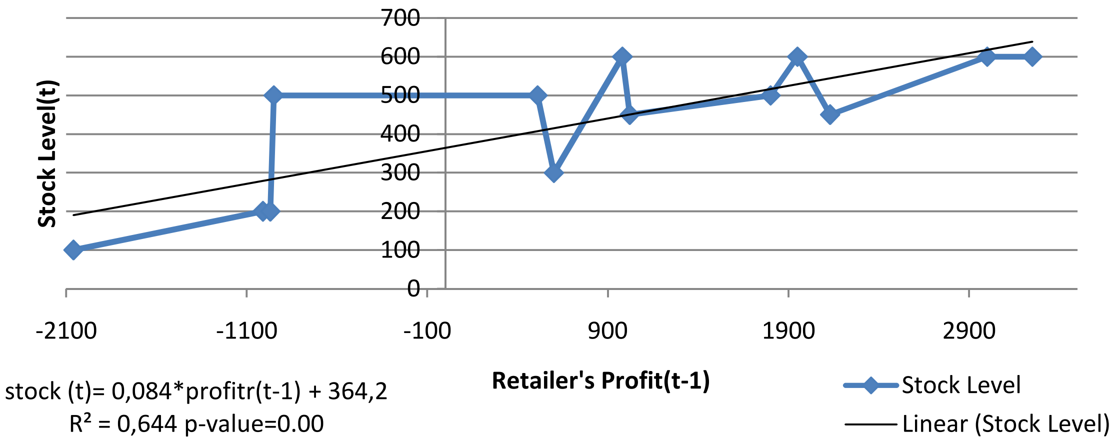



Figure 7.3. Retailer's Stock Level(t) vs. Retailer's Profit(t-1) in Exp. 1a

Figure 7.3 shows that subject 9's stock level decision at period t and his profit at period t-1 are positively related. Beta value is small due to the scale difference between the profit values and stocking values. The model's success in explaining the variance in the stock level decision is large, as indicated by the high $R^2$ value. The p-value is 0, showing that there is a very significant relationship between retailer's stock level decision and his previous period profit. If we know the retailer's profit in period t-1, we can predict his stock level decision at period t successfully. However, "retailer's profit at period t-1" is not indicated as a response variable according to the multiple regression analysis. The reason for that is the high multi-collinearity between retailer's profit and other predictor variables, which resulted with a low tolerance value (0), so that this variable could not enter to any model.

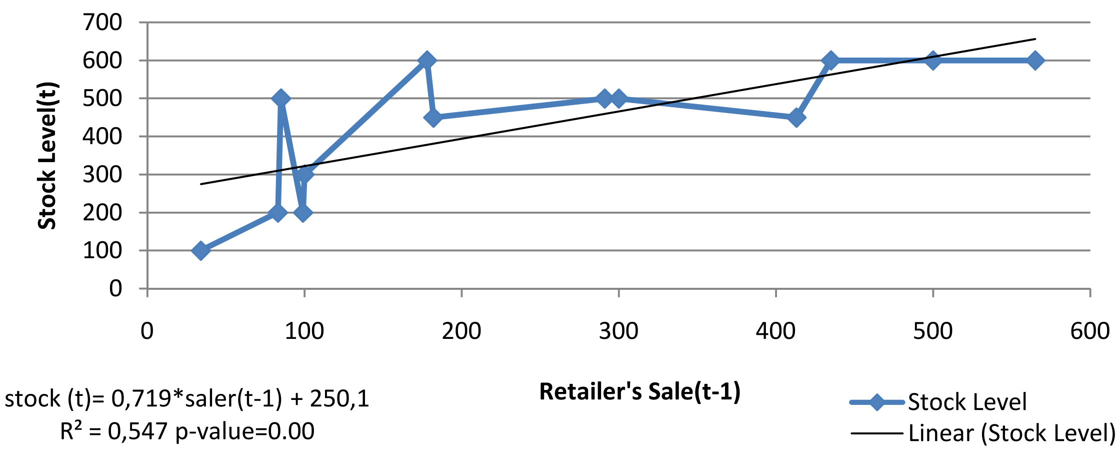



Figure 7.4. Retailer's Stock Level(t) vs. Retailer's Sale(t-1) in Exp. 1a

Figure 7.4 shows that subject 9's stock level decision at period t and his sale at period t-1 are positively related and the beta value is relatively high, showing that a change in the retailer's sale in previous period affects the stock level decision strongly. $R^2$ value of 0.547 indicates that the model's success in predicting the stock level is high. P-value is 0 denoting that the model is very significant (i.e., have no error). This is not surprise as the multiple regression analysis indicated "retailer's sale at period t-1" as a significant predictor variable.

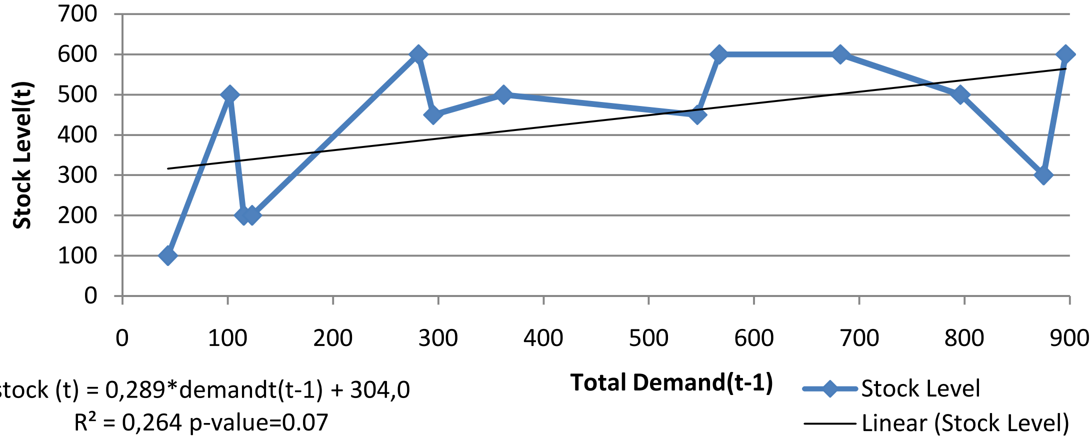



Figure 7.5. Retailer's Stock Level(t) vs. Total Demand(t-1) in Exp. 1a

Figure 7.5 shows that subject 9's stock level decision at period t and total demand at period t-1 are positively related. $R^2$ value indicates a low prediction power of the total demand. P-value is less than 0.1, so we reject the null hypothesis that there is no relationship between total demand at period t-1 and retailer's stock level decision at period t. This is the result we obtained from the multiple regression analysis that "total demand at period t-1" is a significant response variable.

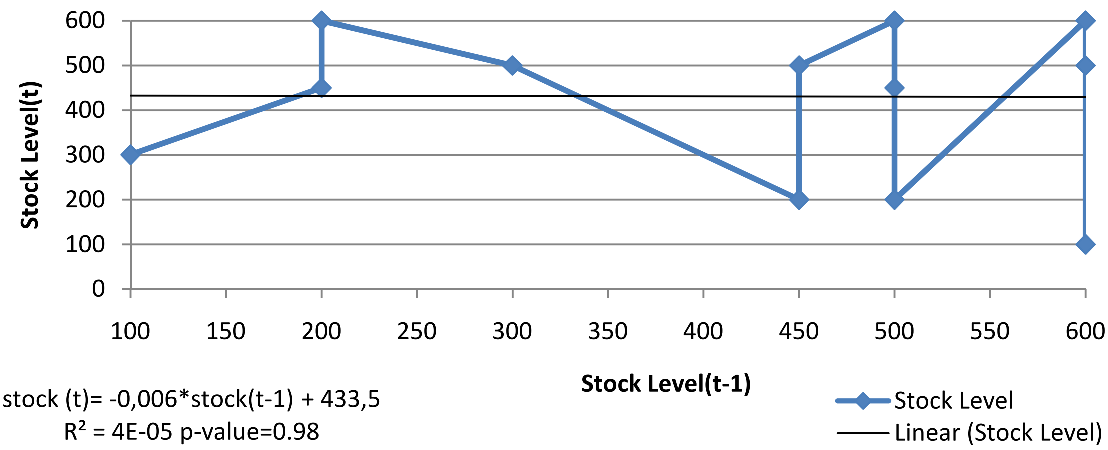



Figure 7.6. Retailer’s Stock Level(t) vs. Stock Level(t-1) in Exp. 1a

Figure 7.6 shows that subject 9’s stock level decision at period t and stock level at period t-1 are negatively related. However, the beta value is so small that we can assume that there is no relationship between them. $R^2$ value of this regression (4E-05) is very small and p-value is very high, indicating that the model is not accepted.

To sum up, the simple linear regression analysis results of subject 9 in experiment 1a indicate that he responded his previous period profit and sale, and previous period total demand when he made his decisions.

Table 7.7 presents our initial estimations of the sign of the relationship between each predictor variable and the dependent variable.

Table 7.7. Expected Sign of the Relationship between Each Predictor Variable and Stock Level Decision

| Variable | Expected Sign of the Relationship |
|---|---|
| stock level at period t-1 | + |
| total demand at period t-1 | + |
| retailer's sale at period t-1 | + |
| retailer's profit at period t-1 | + |
| lost-retailer demand at period t-1 | + |
| overage at period t-1 | - |
| wholesale price at period t | - |

Only in some of the cases, we observed these full set of expectations to hold. For the other cases, at least one predictor variable had the opposite effect or it is not possible to define the relationship[12].

Next, we checked if there exists consistency among subjects regarding the beta signs. We detected some subjects who have the same sign combination in an experiment. Table 7.8. presents the signs of beta coefficients for all subjects in experiment 1c. We observe that subjects 0, 7 and 9 have the same set of signs.

Table 7.8. Sign of the Relationship between Each Predictor Variable and Stock Level Decision in Experiment 1c

| | Subjects | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| stock level(t-1) | + | N/A | N/A | + | N/A | - | - | + | + | + |
| total demand (t-1) | - | N/A | N/A | + | N/A | + | + | - | + | - |
| retailer's sale (t-1) | + | N/A | N/A | + | N/A | + | N/A | + | + | + |
| retailer's profit (t-1) | - | N/A | N/A | - | N/A | + | + | - | - | - |
| lost-retailer demand (t-1) | - | N/A | N/A | - | N/A | + | - | - | + | - |
| overage (t-1) | + | N/A | N/A | + | N/A | - | - | + | + | + |

Table 7.9. Sign of the Relationship between Each Predictor Variable and Stock Level Decision in Experiment 1b

| | Subjects | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| stock level(t-1) | + | + | + | - | + | - | + | - | - | + |
| total demand (t-1) | + | - | + | + | - | - | - | + | + | + |
| retailer's sale (t-1) | + | + | + | + | - | - | - | + | - | + |
| retailer's profit (t-1) | + | + | + | + | - | - | - | + | - | + |
| lost retailer demand (t-1) | - | N/A | + | + | N/A | - | - | + | + | + |
| overage (t-1) | + | + | - | - | + | + | + | - | - | - |

[12] The sign of the relationship between each predictor variable and stock level decision for all subjects in each experiment is available from the authors.

On the contrary, for some experiments it is possible to find two subjects that have inverse signs of each other for each variable. Table 7.9 illustrates this for experiment 1b, subjects 5 and 9.

Finally, we wanted to see if the same subject had the same responses to a given variable among different experiments in a given session. We found differences. This makes sense because different experiments mean different parameter sets. Table 7.10 and Table 7.11 illustrate this for subject 7 in session 1 and subject 9 in session 7, respectively.

Table 7.10. Sign of the Relationship between Each Predictor Variable and Stock Level Decision for Subject 7 in Session 1

| Variable | Exp 1a | Exp 1b | Exp 1c |
|---|---|---|---|
| stock level (t-1) | + | - | + |
| total demand (t-1) | - | + | - |
| retailer's sale (t-1) | - | + | + |
| retailer's profit (t-1) | - | + | - |
| lost-retailer demand (t-1) | - | + | - |
| overage (t-1) | + | - | + |

Table 7.11. Sign of the Relationship between Each Predictor Variable and Stock Level Decision for Subject 9 in Session 7

| Variable | Exp 7a | Exp 7b |
|---|---|---|
| stock level(t-1) | + | - |
| total demand (t-1) | + | - |
| retailer's sale (t-1) | + | - |
| retailer's profit (t-1) | + | - |
| lost-retailer demand (t-1) | + | - |
| overage (t-1) | + | + |

In conclusion, there is not a general trend in subjects' behavior when they decide on the stock level decision. Most of the subjects did not respond according to our expectations.

### 7.1.4. Autocorrelation Analysis

In some of our analysis, we observed that the subjects' stock level decisions are not related with the seven predictor variables significantly. This result encouraged us to investigate other factors to affect the subjects' stock level decisions. Thus, we analyzed if the stock level decisions of the subjects are affected from their own stock level decisions in previous periods. To do this, we conducted subject-based autocorrelation analysis for all experiments.

In statistics, autocorrelation of a variable describes the correlation between the values of that variable in different two time points, as a function of these time points. "Lag t" indicates the time period distance of the compared values of the variable.

In Appendix L, we provide our autocorrelation analysis results for each subject in each experiment. Correlation values are presented for first three lags. Significance indicates the p-value at the first lag obtained by conducting the Box-Ljung test. The Box-Ljung is a statistical test, which is based on autocorrelation plot, and tests the overall randomness based on a number of lags. By using this test, the null hypothesis of "the data is random" (i.e., the decisions are independent) is tested.

Analyzing our results, we conclude that there is not enough evidence to say that the subjects' stock level decisions are affected from their own stock level decisions in any of the previous three periods significantly. However, there are some cases, in which a subject's decision is highly related to his previous period decision. All of these cases are found to be statistically significant at the first lag with a significance value of less than 0.05 with the Box-Ljung test. This is not surprising because most of these cases resulted with a significant response of the manufacturer to stock level at period t-1 in multiple regression analysis. Moreover, by conducting autocorrelation analysis, we managed to explain the behavior in two new cases. Although multiple regression analysis did not indicate any significant result for these cases, autocorrelation analysis indicated that they affected from their own previous period stock level when making their decisions.

## 7.2. Manufacturer's Delivery Lead Time Decision

Here, we analyze manufacturer subjects' delivery lead time decisions in order to find the behavioral reasons underlying their decisions. First, we control whether there is a significant relationship between the delivery lead time decision and other variables. We control the relationship with multiple and simple regression analysis for each experiment and each subject. Second, we control whether there is a significant relationship of each subject's delivery lead time decision at a period with his decisions at the previous periods. To do this, we make an autocorrelation analysis.

### 7.2.1. Multiple Linear Regression Analysis

We analyzed if the subjects are affected from the changes in other variables when they set delivery lead time. For analyzing the relationship between the manufacturer's delivery lead time decision and the other variables, and measuring the effect of each variable on the manufacturer's delivery lead time decision, we used multiple linear regression as the method and SPSS as the statistical tool. As the variable selection method, we used "backward". We worked on all experiments and conducted regression analysis to regress "the manufacturer's delivery lead time decision at period t" with 6 different predictor variables. These variables and their abbreviations used in regression result tables are shown below in Table 7.12. We tested the null hypothesis that there is no relationship between manufacturer's delivery lead time decision and the variables stated in the table. The predictor variable "wholesale price at period t" is only considered for the w-setting experiments.

Table 7.12. Predictor Variables for Multiple Linear Regression Analysis of Manufacturer's Delivery Lead Time Decision

| Variable | Abbreviation |
|---|---|
| manufacturer's profit at period t-1 | profitm |
| manufacturer's sale (direct channel sale) at period t-1 | salem |
| total demand at period t-1 | demandt |
| total sale at period t-1 | salet |
| delivery lead time at period t-1 | time |
| wholesale price at period t | wprice |

In addition to stated predictor variables in the table, we had considered "manufacturer's profit from direct channel at period t-1" and "manufacturer's profit from retailer at period t-1" as other candidates for predictor variables. However, the analysis that included these variables did not result in significant regression equations for some of the cases. This was due to high multi-collinearity between the predictor variables. First, manufacturer's profit is sum of manufacturer's profit from direct channel and manufacturer's profit from retailer. Hence, these three variables cannot be used as predictors all together. Second, manufacturer's profit from direct channel is highly correlated with manufacturer's sale (i.e., his sale in the direct channel). Third, as the direct channel demand is a ratio of total demand and correlated with manufacturer's profit from direct channel, manufacturer's profit from direct channel is also highly correlated with total demand. As a result, we decided to remove these variables from our analysis.

The analysis is conducted for two different data: experiment-based (where all subjects' data is collected together to see the general trend) and subject-based (to investigate subject-based decisions). In subject-based investigations, we analyzed each experiment data for each subjects' decisions separately.

Experiments, which include at least 70% of the time the same delivery lead time decision, were excluded from the experiment-based analysis. Similarly, subjects who chose at least 70% of the time the same delivery lead time in a given experiment were excluded from the subject-based analysis. For such experiments or subjects, $R^2$ values might be artificially high; however, these $R^2$ values do not convey meaningful information. These are stated as "Discarded" in the regression result tables.

For all of the variables stated in regression result tables, the VIF statistic is less than 10. We discarded the variables with a VIF more than 10 to avoid the effect of multi-collinearity.

#### 7.2.1.1. Experiment-based Analysis

Results are shown in Table 7.13. The column "Ses." presents the session and "Exp." presents the experiment. If the delivery lead time decision is expressed by an equation of at least one predictor variable significantly (i.e., if the regression model passed the F test and p-value $\leq$ 0.1), the "response" for that experiment is defined as "yes". "Response variables" show which predictor variables are in the regression model. We also provide $R^2$, the adjusted $R^2$ and F-test p-values. "Equation" shows the regression model of the significant analysis, where p-value is less than 0.1. Absolute regression coefficient (absolute beta values) of each predictor variable in an equation indicates the power of that variable in predicting the delivery lead time decision.

Table 7.13. Experiment-based Multiple Regression Analysis of Delivery Lead Time Decision

| Ses. | Exp. | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1 | 1a | yes | time | 0.295 | 0.289 | 0.000 | time = 8.772 + 0.447*time |
| | 1b | yes | time | 0.390 | 0.384 | 0.000 | time = 10.468 + 0.603*time |
| | 1c | yes | time | 0.322 | 0.316 | 0.000 | time = 4.568 + 0.562*time |
| 2 | 2a | yes | time, profitm, demandt | 0.376 | 0.362 | 0.000 | time = 4.508 + 0.7*time - 0.016*demandt + 0.003*profitm |
| | 2b | yes | time | 0.591 | 0.588 | 0.000 | time = 5.807 + 0.843*time |
| | 2c | yes | time | 0.606 | 0.603 | 0.000 | time = 4.406 + 0.510*time |
| 3 | 3a | yes | time | 0.665 | 0.661 | 0.000 | time = 3.613 + 0.818*time |
| | 3b | yes | time, profitm, salem | 0.362 | 0.343 | 0.000 | time = 44.661 + 0.428*time - 0.009*profitm - 0.114*salem |
| | 3c | yes | time, profitm | 0.477 | 0.465 | 0.000 | time = 7.308 + 0.543*time - 0.001*profitm |
| 4 | 4a | yes | time | 0.224 | 0.221 | 0.000 | time = 13.486 + 0.508*time |
| | 4b | yes | salet, time, salem | 0.372 | 0.362 | 0.000 | time = 17.618 + 0.472*time - 0.012*salet + 0.005*salem |
| 5 | 5a | yes | time | 0.232 | 0.226 | 0.000 | time = 16.381 + 0.403*time |
| | 5b | yes | time, demandt, salem | 0.522 | 0.507 | 0.000 | time = 11.584 + 0.528*time + 0.016*demandt - 0.103*salem |
| 6 | 6a | yes | time, profitm | 0.265 | 0.257 | 0.000 | time = 9.801 + 0.489*time + 0.000*profitm |
| | 6b | yes | time | 0.223 | 0.216 | 0.000 | time = 7.065 + 0.588*time |
| 7 | 7a | yes | time, wprice | 0.911 | 0.910 | 0.000 | time = 5.860 + 0.947*time -1.207*wprice |
| | 7b | Discarded | | | | | |

The analysis shows that set of factors that affect the decisions depend on the experiment. However, previous period delivery lead time is a significant variable that affects the delivery lead time decision in all of the experiments, and the most strong predictor variable in most of the experiments. In other words, a change in this variable affects the manufacturer's decision most. High absolute beta values of the "delivery lead time at period t-1" indicate this effect. In contrast to the stock level analysis results, wholesale price in the current period is not a significant variable in all of the w-setting experiments.

Experiment-based results give an idea on how most of the subjects behaved in a given experimental setup. The significance is 0 for all of the experiments, indicating that the model rejects the null hypothesis that there is a no relationship between the delivery lead time decisions and stated response variables strongly. The $R^2$ values are high, showing the success of the model in predicting the delivery lead time.

#### 7.2.1.2. Subject-based Analysis

The regression analysis results of the subject-based experiments are provided in Appendix M. Here we provide a summary of our observations The subject-based regression analysis shows different results depending on the subject and experiment. The most important observation is that we can talk of a significant variable that affects most subjects' delivery lead time decision consistently, in general. This variable is previous period delivery lead time. Experiment-based results were a sign of this result. Besides, there are some variables, which are responded by all subjects in a given experiment. These include wholesale price in experiment 7a, manufacturer's profit in experiment 5a, and delivery lead time in experiments 1c, 2c and 3a.

We obtained some more specific observations from the subject-based analysis. First, we can trust on the models in predicting the subjects' behaviors. This fact is due to high prediction power (i.e., the $R^2$ values are greater than 0.5) and low significance of the models (i.e., the p-vales are less than 0.05) for most of the cases.

Second, response of subjects to our predictor variables depends on the subjects, the experimental environment (the parameter sett) and the type of the experiment. An example of subjects' differing behavior in the same experiment can be observed in experiment 1b in which there are some subjects whose response to a particular variable is positive and other subjects whose response is negative. An example for subjects being sensitive to experimental environment is subject 9 in session 1. He did not respond to any variable in experiment 1a and 1c; however, he responded to a variable in experiments 1b. This observation is the common behavior of some subjects in sessions 1, 2 and 3. An example for the effect of experiment type is the situation in session 4.

When we compare the results in experiment 4a with 4b, we observe that the same subjects responded differently. This is because experiment 4a is a w-setting experiment, while, experiment 4b is a given-w experiment.

Third observation is about w-setting experiments (i.e., 4a, 5a, 6a and 7a). In these experiments, not all manufacturer subjects responded to the wholesale price in contrast to the retailer subjects when they decide on their stage II decisions. However, the wholesale price is the most powerful predictor of the delivery lead time decisions as in the analysis results of the stock level decisions. This is not surprising because the wholesale price is related to the same period, and hence, directly affects the profit structure of the manufacturer, whereas the other predictor variables are related to the previous period. Another observation is on the sign of the relationship. In experiment 7a, all subjects responded to wholesale price negatively. However, in experiments 4a, 5a and 6a, the relationship between the delivery lead time and wholesale price is not always negative; even all responses are in positive direction in experiment 4a. The manufacturer's optimal strategy in these experiments, which is ER in experiment 7a, CP in experiment 6a, and SP in experiments 4a and 5a might explain this change.

We also detected groups of subjects (1) who responded to the same variables in a given experiment, and (2) who responded to the same variables in different experiments of the same session. Some examples of the first situation are observed in experiments 1b, 3b and 4a. In experiment 1b, subjects 2, 3 and 5 only responded to delivery lead time, in experiment 3b, subjects 0 and 4 only responded to total demand, and in experiment 4a, subjects 8 and 13 responded to both delivery lead time and manufacturer's profit. An example of the second situation is observed in session 2. Subjects 4 and 6 only responded to delivery lead time in all experiments of this session.

### 7.2.2. Simple Linear Regression Analysis

We also conducted simple linear regression analyses between the delivery lead time decision and each predictor variable alone. We tested the null hypothesis that there is no relationship between the delivery lead time decision and the predictor variable. As an example, we provide the analysis on subject 1 in experiment 7b. We knew from the multiple linear regression analysis that subject 1 responded to one predictor variable in Experiment 7b resulting in a multiple regression equation of delivery time(t) = 7.288 -

0.005*total sale(t-1) with an $R^2$ of 0.430 and p-value of 0.011. Related data is provided in Table 7.14.

Table 7.14. Subject 1's Regression Data in Experiment 7b

| Delivery Lead Time (t-1) | Total Demand (t-1) | Manufacturer's Sale (t-1) | Manufacturer's Profit (t-1) | Total Sale (t-1) | Delivery Lead Time (t) |
|---|---|---|---|---|---|
| 50 | 518 | 41 | 242 | 41 | 10 |
| 10 | 88 | 35 | 110 | 35 | 8 |
| 8 | 8 | 4 | -132 | 4 | 10 |
| 10 | 519 | 208 | 1148 | 208 | 7 |
| 7 | 98 | 56 | 132 | 56 | 6 |
| 6 | 672 | 448 | 2410 | 448 | 5 |
| 5 | 654 | 523 | 2738 | 523 | 4 |
| 4 | 854 | 854 | 4499 | 854 | 4 |
| 4 | 666 | 656 | 3371 | 666 | 4 |
| 4 | 231 | 231 | 761 | 231 | 3 |
| 3 | 372 | 368 | 1121 | 372 | 4 |
| 4 | 77 | 77 | -163 | 77 | 4 |
| 4 | 820 | 820 | 4295 | 820 | 4 |
| 4 | 696 | 696 | 3551 | 696 | 4 |

Below in figures, the relationship between each predictor variable and subject 1's deliver lead time decision are plotted. The regression equations, $R^2$ and p-values are also provided.

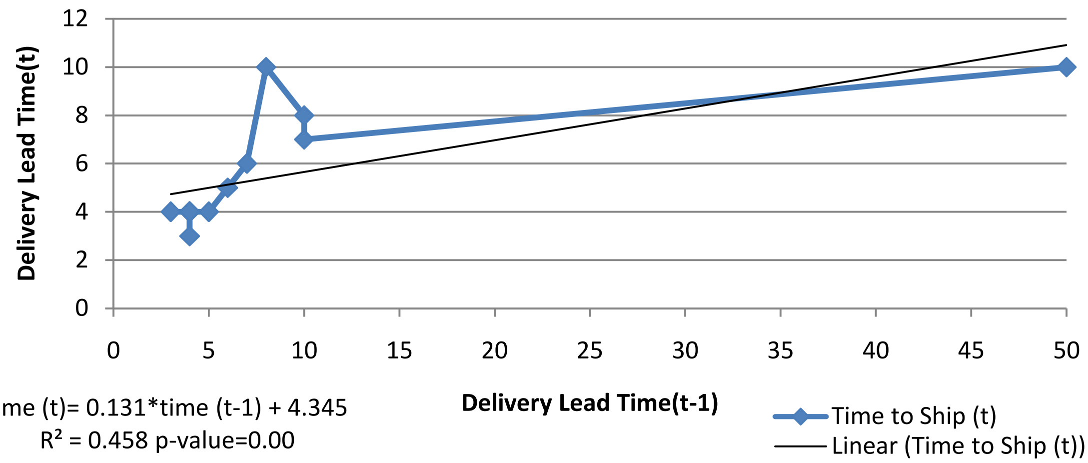



Figure 7.7. Manufacturer's Delivery Lead Time(t) vs. Delivery Lead Time(t-1) in Exp 7b

Figure 7.7 shows that subject 1's delivery lead time decision at period t and his delivery lead time decision at period t-1 are positively related. $R^2$ is relatively high, which shows that information on the delivery lead time in the previous period is useful in predicting the next period delivery lead time. P-value is 0 denoting that the relationship is strongly significant. However, "delivery lead time at period t-1" is eliminated from the model in multiple regression analysis. This is not related to the multi-collinearity; whereas, its partial significance is assessed to be more than 0.1.

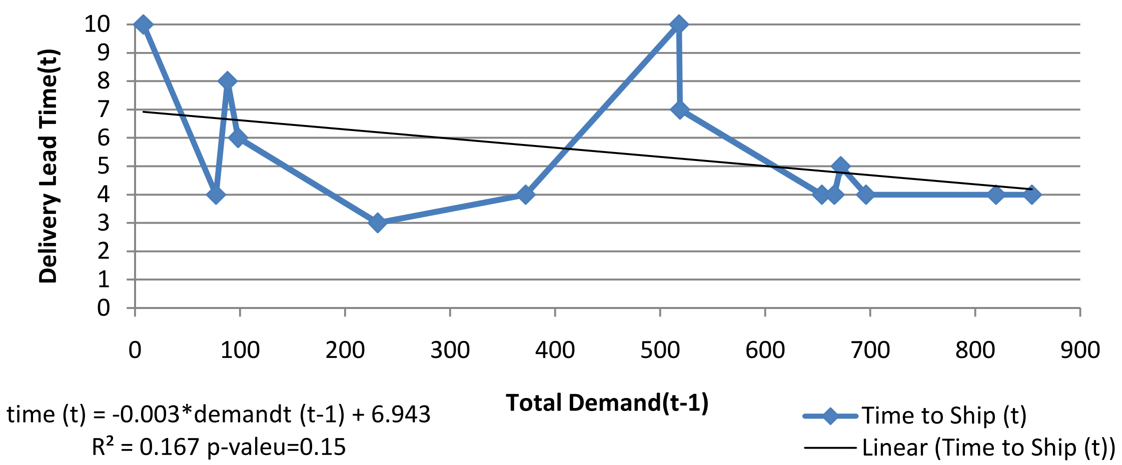



Figure 7.8. Manufacturer's Delivery Lead Time(t) vs. Total Demand(t-1) in Exp. 7b

Figure 7.8 shows that subject 1 is negatively affected from the total demand at period t-1 when he sets his delivery lead time at period t. $R^2$ is denoting that the power of this model in predicting the delivery lead time is not low. However, p-value shows that this relationship is not significant.

There is a negative relationship between subject 1's sale at period t-1 and his delivery lead time decision at period t, as shown in Figure 7.9. High $R^2$ shows that the model is powerful in predicting the delivery lead time and low p-value shows that the relationship is significant. However, low absolute beta value of this variable shows that a unit change in subject 1's direct channel sale affects the delivery lead time decision of subject 1 at a negligible amount. Multiple regression analysis did not indicate "manufacturer's sale at period t-1" as a significant response variable. The fact is due to high multi-collinearity between manufacturer's sale and other variables (especially high correlation with total sale), so that this variable is excluded from the model.

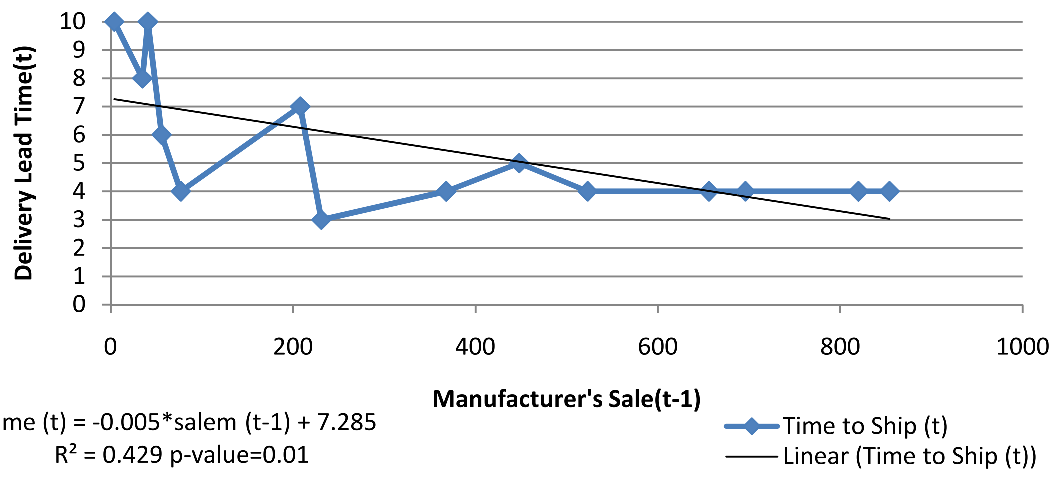



Figure 7.9. Manufacturer's Delivery Lead Time(t) vs. Manufacturer's Sale(t-1) in Exp. 7b

Figure 7.10 shows that subject 1 gives importance on his profit at period t-1, when he sets his delivery lead time at period t, and the relationship between these two variables is negative. The relationship is negative and $R^2$ is relatively high, which indicates the model's success in explaining the variance in delivery lead time decision. P-value is less than 0.01 indicating that the relationship is significant. The reason for the small absolute beta value is the scale difference between delivery lead time and profit values. This variable is not stated to be a significant response variable in multiple regression analysis due to high multi-collinearity between manufacturer's profit and total sale.

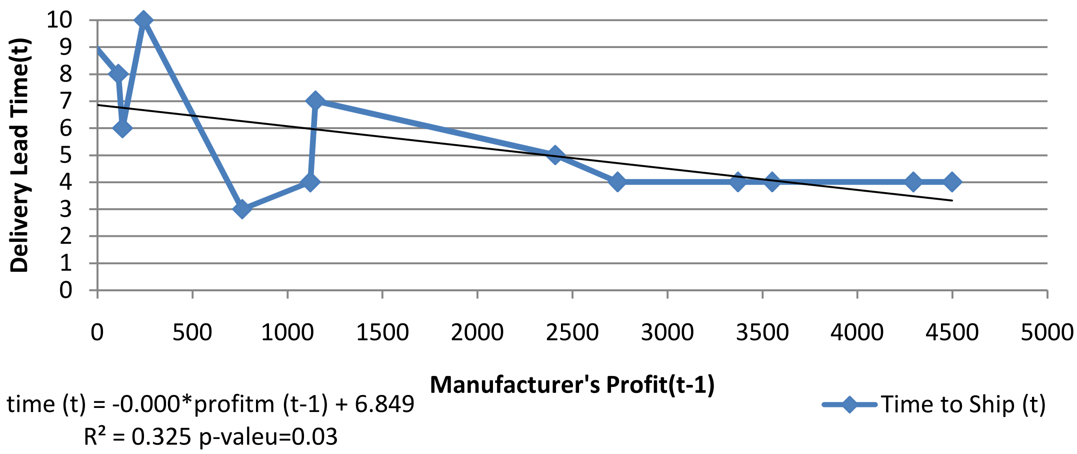



Figure 7.10. Manufacturer's Delivery Lead Time(t) vs. Manufacturer's Profit(t-1) in Exp. 7b

In addition, subject 1 gives a high importance on total sale at period t-1, when he sets his delivery lead time at period t. There is a negative and strong relationship between delivery lead time at period t and "total sale at period t-1" for subject 1, as seen in Figure 7.11. This is the result of multiple regression analysis with a $R^2$ of 0.430 and p-value of 0.01.

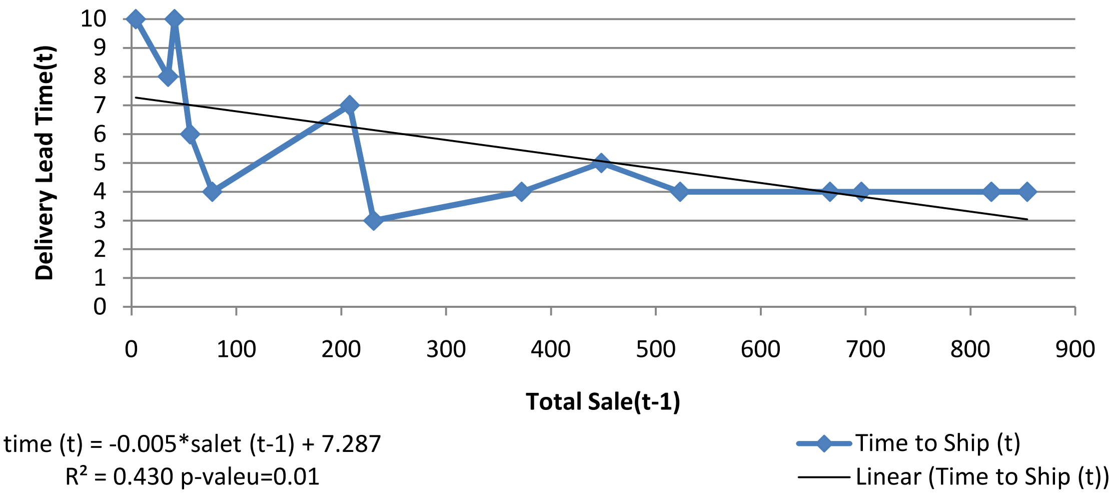



Figure 7.11. Manufacturer's Delivery Lead Time(t) vs. Total Sale(t-1) in Exp. 7b

As seen from figures above, although the multiple regression analysis resulted with only one significant variable for subject 1 in experiment 7b, there are some other variables, which affect the subject's delivery lead time decision and can be used in prediction of his decisions.

We observed that some subjects improved their delivery lead time decision by time. For instance, subject 0 in experiment 1c, subjects 2 and 3 in experiment 3c, subjects 7 and 9 in experiment 7a, and subjects 1 and 7 in experiment 7b decreased their delivery lead time decision over periods. As the theoretical optimal strategy of the manufacturer is *ER* in these experiments, these subjects might have learned how to make better decisions by time.

Table 7.15 below presents our initial estimations of the sign of the relationship between each predictor variable and delivery lead time.

Table 7.15. Expected Sign of the Relationship between Each Predictor Variable and Delivery Lead Time

| Variable | Expected Sign of the Relationship |
|---|---|
| manufacturer's profit (t-1) | - |
| manufacturer's sale (t-1) | - |
| total demand (t-1) | - |
| total sale (t-1) | - |
| delivery lead time (t-1) | + |
| wholesale price (t) | - |

Only in some of the cases, we observed these full set of expectations to hold. In addition, none of the subjects responded according to our expectations in three experiments (i.e., experiments 2c, 4a and 6a)[13].

Next, we checked if there exists consistency among subjects regarding the beta signs. We detected some subjects who have the same sign combination in an experiment. Table 7.16 presents the signs of beta coefficients for all subjects in experiment 1a. There are three set of subjects in which the subjects have the same set of signs.

Table 7.16. Sign of the Relationship between Each Predictor Variable and Delivery Lead Time Decision in Experiment 1a

| | Subjects | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| delivery lead time (t-1) | - | + | - | - | + | + | + | + | + | - |
| total demand (t-1) | + | + | + | + | - | + | - | + | - | + |
| manufacturer's sale (t-1) | + | - | + | + | - | + | - | + | - | + |
| manufacturer's profit (t-1) | + | - | + | + | - | + | - | + | - | + |
| total sale (t-1) | + | + | + | + | - | + | - | + | - | + |

On the contrary, for some experiments it is possible to find two subjects that have inverse signs of each other for each variable. Table 7.17 illustrates this for experiment 6b, where subjects 2 and 3 behaved different from subjects 0, 5 and 7.

[13] The sign of the relationship between each predictor variable and delivery lead time decision for all subjects in each experiment is available from the authors.

Table 7.17. Sign of the Relationship between Each Predictor Variable and Delivery Lead Time Decision in Experiment 6b

| | Subjects | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| delivery lead time (t-1) | + | + | - | - | + | + | + | + | - | + |
| total demand (t-1) | + | + | - | - | - | + | - | + | + | - |
| manufacturer's sale (t-1) | + | + | - | - | - | + | - | + | + | - |
| manufacturer's profit (t-1) | + | - | - | - | - | + | - | + | + | - |
| total sale (t-1) | + | - | - | - | - | + | - | + | + | - |

Finally, we wanted to see if the same subject had the same responses to a given variable among different experiments in a given session. We found differences. This makes sense because different experiments mean different parameter sets. Table 7.18 shows how the behavior of subject 0 in session 1 changed from one experiment to another.

Table 7.18. Sign of the Relationship between Each Predictor Variable and Delivery Lead Time for Subject 0 in Session 1

| Variable | Exp. 1a | Exp. 1b | Exp. 1c |
|---|---|---|---|
| delivery lead time (t-1) | - | - | + |
| total demand (t-1) | + | + | - |
| manufacturer's sale (t-1) | + | - | - |
| manufacturer's profit (t-1) | + | + | - |
| total sale (t-1) | + | - | - |

In conclusion, there is not a general trend in subjects' behavior when they decide on the delivery lead time decision. Most of the subjects did not respond according to our expectations.

### 7.2.3. Autocorrelation Analysis

In some of our analysis, we observed that the subjects' delivery lead time decisions are not related with the 6 predictor variables significantly. This result encouraged us to investigate other factors to affect the subjects' delivery lead time decisions. Thus, we analyzed if the delivery lead time decisions of the subjects are affected from their own delivery lead time decisions in previous periods. To do this, we conducted subject-based autocorrelation analysis for all experiments.

In Appendix N, we provide our autocorrelation analysis results for each subject in each experiment. Correlation values are presented for first three lags. Significance indicates the p-value at the first lag obtained by conducting the Box-Ljung test. We tested the null hypothesis that “the data is random” (i.e., the decisions are independent).

Analyzing our results, we conclude with that there is not enough evidence to say that the subjects’ delivery lead time decisions are affected from their own delivery lead time decisions in any of the previous three periods significantly. However, there are some cases, in which a subject’s decision is highly related to his previous period decision. All of these cases are found to be statistically significant at the first lag with a significance value of less than 0.05 with the Box-Ljung test. This is not surprising because most of these cases resulted with a significant response of the manufacturer to delivery lead time at period t-1 in multiple regression analysis. However, by conducting autocorrelation analysis, we could not explain the behavior in the cases in which our multiple regression analysis did not result with a significant response variable.

# CHAPTER 8

## CHAPTER 8 : CONCLUSION AND FUTURE RESEARCH

Here, we discuss our main results, conclude and mention future research directions.

### 8.1. Conclusion

In this thesis, we studied the dual channel management problem of a manufacturer. Our study is based on the theoretical models of Chen et al. (2008), and Gökduman and Kaya (2009). We analyze manufacturer-retailer interaction under two contract types (i.e., wholesale price contract and buyback contract) through controlled experiments with human subjects to check the validity of our theoretical models and predictions, and to analyze the behavior of subjects.

The three-stage game theoretical dual channel model was previously solved with backwards induction, using analytical as well as computational methods coded with Mathematica. That study identified three types of dual channel strategies for the manufacturer: Eliminate retailer (ER), Capture all Profit (CP) and Share Profit (SP). Each strategy characterizes three aspects of the dual channel relationship: How the market will be segmented, how much each channel will sell and how profits will be shared between the manufacturer and the retailer. We presented the theoretical model in this thesis for completeness, but our focus is on experiments with human decision makers.

One reason why we conducted experiments is to check the validity of the "dual channel strategy recommendations" to the manufacturer. In a way, experiments act as "wind tunnels" to test such business policy changes, often bridging the gap between theoretical predictions and real-life applicability. In this respect, our experiments show that the dual channel models (wholesale price contract and buyback contract models) are overall successful. They can predict the type of manufacturer's strategy for given parameter sets $(k, m, c, p, v)$ representing different market conditions. The models are also successful in predicting the direction of subjects' decisions and results in response to changes in parameter values. The models, however, are not that successful in prediction of the actual decision values. We observe significant deviations from predicted values, and high level of "dispersion" in participants' decisions that do not decrease with "learning" over time. We attribute the deviations to certain "behavioral factors" such as risk aversion, loss aversion and decision heuristics. Note, however, that in this thesis work, we do not "prove" the existence of these behavioral factors we only observe their effects on decisions and speculate. Proving the existence of such factors would require a more in-depth study that is in our future work agenda.

Our model presents s a relatively complex "game" that has two decision stages (stages I and II), one of them containing a simultaneous move game in itself (the stage II operational decisions game). The presence of random total demand further complicates the decision making process for the participants. Within this "complex" game structure, our experiments also serve to two general questions that are of interest to most game-theoretical models: (1) Is Nash Equilibrium a good predictor of the outcome of a simultaneous-move game? (2) When making decision at the first stage of a two-stage game, can a subject foresee the outcome of the second stage, and act accordingly? We find that (1) The Nash Equilibrium is not necessarily a good predictor of the exact decision values, due perhaps to the behavioral biases. However, it is a good predictor of directional changes (2) The participants can anticipate the second stage outcome and act accordingly in relatively simple models (i.e., the wholesale price contract model) but not in more complicated ones (i.e., the buyback contract model).

The central theme in our study is the performance comparison of the buyback contract and wholesale price contracts. The dual channel model with buyback contract gives the manufacturer extensive power in our theoretical model. He can squeeze the retailer with its direct channel horizontally, and at the same time, with the two contract parameters vertically. By choosing the contract parameters at stage I, he sets the "tome of the game" to be played at stage II. Thus, in theory, the manufacturer's contract decisions at stage I determine how consumers will be segmented between the channels, and how risks and profits will be shared with the retailer. Whether the manufacturer can use this power wisely by setting the right contract parameters at stage I is the question. At face value, the buyback contract benefits the retailer by reducing its cost of overage. However, the manufacturer can also play with the wholesale price and make sure that the retailer only gains the minimum acceptable profit. Theory says that the manufacturer can achieve high market coverage and high profit with the buyback contract, and leave the retailer with limited profit. What we observe is that the manufacturers indeed squeeze the retailer's profit, but are not as successful in improving their own profits. Manufacturers did not offer generous buyback prices, and as a result, retailers did not order as much. In some cases, manufacturers made more use of their direct channel than necessary.

Our observations on the total supply chain profit are similar. In theory, the dual channel structure improves total supply chain profits through serving heterogeneous consumers with two different channels. In our theoretical model, the time-sensitive consumers prefer to buy from the retail channel, while the less-time-sensitive consumers prefer to buy from the direct channel. The total supply chain profit is directly related to the number of customers served. If the retailer stocks sufficient quantity, and if the manufacturer sets a reasonable delivery lead time, the total number of lost customers would be minimized. In theory, the buyback contract complements this benefit of dual channels by making the retailer order more units. In our experimental study, however, because the manufacturers could not set high-enough buyback prices, this benefit went mostly unrealized.

Our study has a number of weaknesses. One such weakness is that the experiments take around 2.5 hours, which places some cognitive burden on the participants. Although we observed that the participants did not lose focus during the experiments, this is an issue to be considered in future studies. Another weakness is that we used two different set of participants in our WPCE and BCE experiments (i.e., a between-subjects design). We could have obtained sharper results if we compared the results of the same subject set between the two studies (i.e., a within-subject design). However, using the same subject set in two studies would cause significant "learning effect". The experience level of participants from one study might affect their behavior in the other study. This is a classical trade-off in such experimental studies, and we chose the "between subjects" alternative for our work.

## 8.2. Future Research Directions

This study can be extended in a number of ways. Here we provide only a number of examples. First, we observed that the theoretical model is not successful in predicting the quantitative decisions, because there is bias in human decision-makers' decisions. One can change our model to another form, which captures the human decision bias. For example, the utility functions of the decision makers can be modified to allow "risk aversion". Second, we studied the wholesale price and buyback contracts. Other contracts including quantity discount, revenue sharing or rebates can also be considered. Third, the model setting can be changed to include other dual channel environment factors into account; such as competition between multiple manufacturers or retailers, and other combinations of channel ownership and structure such as retailers operating online stores or manufacturers operating physical stores.

The experimental study can also be modified in a number of ways. First, to obtain a less complex game for participants, the total demand might be fixed at some value. Recall that the demand faced by a particular channel would still be "unknown" in advance because the total demand is shared between the channels based on the service level decisions of the two players. Removing the stochastic nature of the total demand would make the game less realistic, however, more manageable for participants. We believe that we will observe less dispersion and more learning in this version of the game. Second, we considered the total demand to be uniformly distributed. One can also study alternative total demand distributions such as normal distribution. This change can easily be implemented in the experimental study; however, it would be difficult in the theoretical study. One can perhaps resort to numerical methods to solve the model with different demand distributions. Third, to study the role of a "long-run partnership" between the firms, we may make the same manufacturer-retailer couples to play in all periods of an experiment. We expect the players to act "strategically" in the initial periods, leading to interesting results regarding collaboration, threats, punishments and reputation. Fourth, we can provide a more "visual" decision support tool to help subjects' decision-making process. The current decision support tool presents the results in a table format, which may not be easy for the subjects to comprehend. Fifth, one can conduct more experiments using the current setting to strengthen existing results. This includes conducting WPCE experiments with Sabanci University students. Finally, one can further analyze data from the current (and possibly new) experiments to address other questions of interest. For example, to study differences due to cultural factors, the decisions of Turkish and American students within the same experimental setting can be compared.

# BIBLIOGRAPHY


Agatz, N., M. Fleischmann. 2008. E-fulfillment and multi-channel distribution: A review. *European Journal of Operational Research* 187 339-356.

Akcura, M. T., K. Srinivasan. 2005. Research note: Customer intimacy and cross-selling strategy. *Management Science* 51(6) 1007-1012.

Allen, L., D. M. Cooperstein, D. Young, T. Oum, J. Lee. 2000. Channel conflict crumbles. *Forrester Research,* (March).

Alptekinoglu, A., C. S. Tang. 2005. A model for analyzing multichannel distribution systems. *European Journal of Operational Research* 163(3) 802-824.

Amaldoss, W., T. H. Ho, A. Krishna, K. Y. Chen, P. Desai, G. Iyer, S. Jain, N. Lim, J. Morgan, R. Oprea, J. Srivasatava. 2008. Experiments on strategic choices and markets. *Springer Science & Business Media* 19 417-429.

Asdemir, K., V. S. Jacob, R. Krishnan. 2002. Dynamic pricing of home delivery. Working Paper, The University of Texas at Dallas, Richardson, TX.

Barlas, Y, M. G. Özevin. 2004. Analysis of stock management gaming experiments and alternative ordering formulations. *Systems Research and Behavioral Science* 21 439-470.

Becker-Peth, M., E. Katok, U. W. Thonemann. 2009. Designing contracts for irrational but predictable newsvendors. Working Paper.

Bendoly, E., R. Croson, P. Goncalves, K. Schultz. 2010. Bodies of knowledge for research in behavioral operation. *Production and Operations Management* 19(4).

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

Bernstein, F., F. Chen, A. Federgruen. 2006. Coordinating supply chains with simple pricing schemes: The role of vendor-managed inventories. *Management Science 52* (10) 1483-1492.

Bernstein, F., J. S. Song, X. Zheng. 2009. Free-riding in a multi-channel supply chain. *Naval Research Logistics* 56 745-765.

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

Bolton, G. E., A. M. Kwasnica. 2002. Introduction to the special issue on experimental economics in practice. *Interfaces* 32(5) 1-3.

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

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

Boyaci, T. 2005. Competitive stocking and coordination in a multiple channel distribution system. *IIE Transactions* 37 407–427.

Brace, N., R. Kemp, R. Snelgar. 2006. *SPSS for Psychologists.* Lawrence Erlbaum Associates, Mahwah, NJ.

Brooker, K. 1999. E-rivals seem to have home depot awfully nervous. *Fortune* 140 (16) 28–29.

Brynjolfsson, E., M. Smith. 2000. Frictionless commerce: A comparison of internet and conventional retailers. *Management Science* 46 563-585.

Cachon, G. P. 2003. Supply chain coordination with contracts. A. G. de Kok, S. C. Graves, eds. Chapter 6 In *Handbooks in Operations Research and Management Science: Supply Chain Management*. North-Holland, Amsterdam, The Netherlands, 229-340.

Cachon, G., M. Lariviere. 2005. Supply chain coordination with revenue sharing: Strengths and limitations. *Management Science* 51 (1) 30–44.

Cai, G., Z. G. Zhang, M. Zhang. 2009. Game theoretical perspectives on dual-channel supply chain competition with price discounts and pricing schemes. *International Journal of Production Economics* 117 80-96.

Cairncross, F. 1997. *The Death of Distance*. Harvard University Press, Cambridge, MA.

Carlton, D. W., J. A. Chevalier. 2001. Free riding and sales strategies for the internet. National Bureau of Economic Research, Working Paper 8067.

Cattani, K., W. Gilland, H. S. Heese, J. Swaminathan. 2006. Boiling frogs: Pricing strategies for a manufacturer adding a direct channel that competes with the traditional channel. *Productions and Operations Management* 15(1) 40-56.

Cattani, K. D., W.G. Gilland, J. M. Swaminathan. 2004. Coordinating traditional and internet supply chains. D. Simchi-Levi, D. Wu, M. Shen, eds. Chapter 21 In *Supply Chain Analysis in the e-Business Era*. Kluwer Academic Publishers, Boston, MA.

Chen, F., A. Federgruen, Y. S. Zheng. 2001. Coordination mechanisms for a distribution system with one supplier and multiple retailers. *Management Science* 47(5) 693-708.

Chen, K. Y., M. Kaya, O. Özer. 2008. Dual sales channel management with service competition. *Informs* 10(4) 654-675.

Chiang, W. K. 2010. Product availability in competitive and cooperative dual-channel distribution with stock-out-based substitution. *European Journal of Operational Research* 200 111-126.

Chiang, W. K., D. Chhajed, J.D. Hess. 2003. Direct marketing, indirect profits: A strategic analysis of dual channel supply chain design. *Management Science* 49(1) 1-20.

Chiang, W. Y. K., G. E. Monahan. 2005. Managing inventories in a two-echelon dual-channel supply chain. *European Journal of Operational Research* 162 325-341.

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

Croson, D. C., R. Croson, Y. Ren. 2008. How to manage an overconfident newsvendor. Working Paper, CBEES.

Croson, R., K. Donohue. 2002. Experimental economics and supply chain management. *Interfaces* 32(5) 74-82.

Croson, R., K. Donohue. 2003. Impact of post data sharing on supply chain management: An experimental study. *Productions and Operations Management* 12(1) 1-11.

Croson, R., K. Donohue. 2005. Behavioral causes of the bullwhip effect and the observed value of inventory information. *Management Science* 00(0) 1-14.

Croson, R., S. Gächter. 2010. The science of experimental economics. *Journal of Economic Behavior & Organization* 73(1) 122-131.

Donohue, K. 1996. Supply contracts for fashion goods: Optimizing channel profits. The Wharton School, University of Pennsylvania, Philadelphia, PA.

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

Driver, B., Z. Evans. 2004. Channel conflict: Historical perceptions, management implications, and so much more. Working Paper.

Dumrongsiri, A., M. Fan, A. Jain, K. Moinzadeh. 2008. A supply chain model with direct and retail channels. *European Journal of Operational Research* 187 691-718.

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

Forrester Research, 2005. Forrester research US e-commerce forecast: Online retail sales to reach $329 billion by 2010. *http://www.forrester.com.*

Fudenberg, D., J. Tirole. 1991. *Game Theory*. MIT Press, Cambridge, MA.

Ganfu, W., A. Xing-zheng, D. Huaping. 2009. Study on dual channel revenue sharing coordination mechanisms based on free riding. *IEEE Xplore* 532-535.

Geng, Q., S. Mallik. 2007. Inventory competition and allocation in a multi channel distribution system. *European Journal of Operational Research* 182 704-729.

Ghose, A., M. Smith, R. Telang. 2006. Internet exchanges for used books: An empirical analysis of product cannibalization and welfare implications. *Information Systems Research* 17(1) 1-19.

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

Gökduman, S., M. Kaya. 2009. *Dual sales channel management with buyback contracts.* Unpublished thesis. Sabancı University, İstanbul.

Guala, F. 2005. *The Methodology of Experimental Economics*. Cambridge University Press, New York, USA.

Gulati, R., J. & Garino. 2000. Get the right mix of bricks and clicks. *Harvard Business Review,* (May-June).

Guo, L., Y. Liu. 2008. To restrain or to expand: Optimal retail store opening strategies in coping with manufacturer direct entry. Working Paper.

Gupta, A., B. Su, Z. Walter. 2004. An empirical study of consumer switching from traditional to electronic channels: A purchase-decision process perspective. *International Journal of Electronic Commerce* 8(3) 131-161.

Hendershott, T., J. Zheng. 2006. A model of direct and intermediated sales. *Journal of Economics and Management Strategy* 15(2) 279-316.

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

Jeuland, A., S. Shugan. 1983. Managing channel profits. *Marketing Science* 2(3) 239-272.

Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decisions under risk. *Econometrica* 47 313-327.

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

Kaya, M., Ö. Özer. 2008. Risk and information sharing in supply chains through pricing contracts. Ö. Özer, R. Phillips, eds. To appear in *Handbook of Pricing Management*. Oxford Press, Oxford, UK.

Keck, L., A. Marcheva, G. Valen, S. Years. 1998. Channel conflict: The impact of direct internet sales of personal computers on traditional retail channels. Working Paper, Owen Graduate School of Management, Vanderbilt University, Nashville, TN.

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

King, R. C., R. Sen, M. Xia. 2004. Impact of web-based e-commerce on channel strategy in retailing. *International Journal of Electronic Commerce 8*(3) 103-130.

Kremer, M., E. Katok, S. Minner, & L. N. V. Wassenhove. 2007. Decision postponement in supply chains: Value of supply flexibility and utility of waiting. University of Mannheim, Department of Logistics, Technical Report 2.

Kumar, N., R. Ruan. 2006. On manufacturers complementing the traditional retail channel with a direct-online channel. *Quantitative Marketing and Economics* 4 289-323.

Kurata, H., D.Q. Yao, J. Liu. 2007. Pricing policies under direct vs. indirect channel competition and national vs. store brand competition. *European Journal of Operational Research* 180 262-281.

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

Massachusetts Institute of Technology, 2001. Channel Conflict on the Internet. *http://dspace.mit.edu.*

Matsui, A. 1992. Best response dynamics and socially stable strategies. *Journal of Economic Theory* 57 343-362.

Mukhopadhyay, S., D. Yao, X. Yue. 2008. Information sharing of value adding retailer in a mixed channel hi tech supply chain. *Journal of Business Research 9*(61) 950-958.

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

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

Press, W. H., B. P. Flannery, S. A. Teukolsky, W. Vetterling. 1992. *Numerical Recipes in Fortran 77: The Art of Scientific Computing*. Cambridge University Press, Cambridge, UK.

Rhee, B., S. Park. 2000. Online store as a new direct channel and emerging hybrid channel system. Working Paper, The Hong Kong University of Science & Technology.

Ryan, J. K., D. Sun, X. & Zhao. 2008. Coordinating a supply chain with a manufacturer-owned online channel: A dual channel model under price competition. Working Paper.

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

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

Seifert, R. W., U. W. Thonemann, M. A. Sieke. 2006. Integrating direct and indirect sales channels under decentralized decision making. *International Journal of Production Economics* 103 209-229.

Sheffi, Y. 2007. *The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage.* MIT Press, Cambridge, MA.

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

StatSoft. 2010. Electronic Statistics Textbook. Tulsa, OK. *http://www.statsoft.com.*

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

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

Tarn, J. M., M. A. Razi, H. J. Wen, A. A. Perez Jr. 2003. E-fulfillment: The strategy and operational requirements. *Bradford* 16 (5) 350-368.

Taylor, T. 2002. Coordination under channel rebates with sales effort effects. *Management Science* 48 992-1007.

Tirole, J. 1988. *The Theory of Industrial Organization*. MIT Press, Cambridge, MA.

Tsay, A. 1999. Quantity-flexibility contract and supplier-customer incentives. *Management Science* 45 1339-1358.

Tsay, A., N. Agrawal. 2004. Channel conflict and coordination in the e-commerce age. *Production & Operations Management* 13(1) 93-110.

Viswanathan, S. 2005. Competing across technology differentiated channels: The impact of network externalities and switching costs. *Management Science* 51(3) 483-496.

Weng, Z. K. 1995. Channel coordination and quantity discounts. *Management Science* 41 1509-1522.

Wilcoxon, F. 1945. Individual comparisons by ranking methods. Biometrics 1 80-83.

Yan, R. 2008. Profit sharing and firm performance in the manufacturer-retailer dual channel supply chain. *Electron Commerce Research* 8 155-172.

Yan, R. Z. Pei. 2009. Retail services and firm profit in a dual-channel market. *Journal of Retailing and Consumer Services* 16 306-314.

Zhang, X. 2009. Retailer's multichannel and price advertising strategies. *Marketing Science* 28(6) 1080-1094.

# APPENDICES

## Appendix A. Notation

### Exogenous Constants

$v$: Product's value to consumers

$p$: Selling price at both channels

$a$: Maximum market size for the product

$k$: Retailer inconvenience cost

$c$: Unit production cost

$m$: Direct channel cost parameter

### Decision Variables

$\alpha \in [0, 1]$: Retailer's service level

$\phi(\alpha) \in [0, 1]$: Availability level

$q(\alpha)$: Stocking level

$t$: Direct channel's delivery lead time

$w$: Wholesale price

$b$: Buyback price

### Others

$d \in [0,\ 1]$: Consumer time-sensitivity index

$D_d^1$: Primary demand in the direct channel

$D_d^2$: Secondary demand in the direct channel

$D_r$: Demand in the retail channel

$X$: Market size $\sim UNIF\ [0,\ a]$

## Appendix B. The Algorithm of Two-dimensional Kolmogrov-Smirnov Test

Two-dimensional Kolmogorov-Smirnov test on two samples. Given the *x* and *y* coordinates of the first sample as n1 values in arrays x1(1:n1) and y1(1:n1), and likewise for the second sample, n2 values in arrays x2 and y2, this routine returns the two-dimensional, two-sample K-S statistic as “d”, and its significance level as “prob”. Small values of prob show that the two samples are significantly different. Note that the test is slightly distribution-dependent, so prob is only an estimate.

```
SUBROUTINE ks2d2s(x1,y1,n1,x2,y2,n2,d,prob)
INTEGER n1,n2
REAL d,prob,x1(n1),x2(n2),y1(n1),y2(n2)
C USES pearsn,probks,quadct
INTEGER j
REAL d1,d2,dum,dumm,fa,fb,fc,fd,ga,gb,gc,gd,r1,r2,rr,sqen,probks
d1=0.0
do 11 j=1,n1                          // First, use points in the first sample as origins.
        call quadct(x1(j),y1(j),x1,y1,n1,fa,fb,fc,fd)
        call quadct(x1(j),y1(j),x2,y2,n2,ga,gb,gc,gd)
        d1=max(d1,abs(fa-ga),abs(fb-gb),abs(fc-gc),abs(fd-gd))
enddo 11
d2=0.0
do 12 j=1,n2                          // Then, use points in the second sample as origins.
        call quadct(x2(j),y2(j),x1,y1,n1,fa,fb,fc,fd)
        call quadct(x2(j),y2(j),x2,y2,n2,ga,gb,gc,gd)
        d2=max(d2,abs(fa-ga),abs(fb-gb),abs(fc-gc),abs(fd-gd))
enddo 12
d=0.5*(d1+d2)                                              // Average the K-S statistics.
sqen=sqrt(float(n1)*float(n2)/float(n1+n2))
call pearsn(x1,y1,n1,r1,dum,dumm)     // Get the linear correlation coefficient for each sample.
call pearsn(x2,y2,n2,r2,dum,dumm)
rr=sqrt(1.0-0.5*(r1**2+r2**2))
 // Estimate the probability using the K-S probability function probks.
prob=probks(d*sqen/(1.0+rr*(0.25-0.75/sqen)))
return
END
```

## Appendix C. Outlier Data in Wholesale Price Contract Experiments

Table 0.1. Outlier Data in Wholesale Price Contract Experiments

| Exp. | Period | Manufacturer | Retailer | Wholesale Price | Time to Ship | Stock Level |
|---|---|---|---|---|---|---|
| 1a | 3 | 7 | 1 | 4 | 100 | 400 |
| 1b | 6 | 5 | 2 | 6 | 300 | 270 |
| 2a | 30 | 0 | 1 | 4 | 300 | 600 |
| 2b | 20 | 2 | 7 | 6 | 300 | 400 |
| 2b | 21 | 7 | 5 | 6 | 300 | 330 |
| 3a | 3 | 3 | 2 | 2 | 500 | 10 |
| 4a | 23 | 3 | 2 | 2 | 600 | 500 |
| 4b | 1 | 11 | 5 | 3 | 550 | 350 |
| 4b | 8 | 1 | 7 | 3 | 1000 | 415 |
| 4b | 13 | 10 | 0 | 3 | 324 | 234 |
| 4b | 20 | 3 | 8 | 3 | 400 | 200 |
| 5a | 16 | 5 | 3 | 3 | 350 | 345 |
| 5a | 29 | 5 | 1 | 3 | 350 | 250 |
| 5b | 27 | 2 | 3 | 3 | 300 | 333 |
| 5b | 22 | 7 | 5 | 3 | 1 | 369 |
| 5b | 21 | 7 | 6 | 3 | 0 | 340 |
| 5b | 20 | 6 | 5 | 3 | 0 | 777 |
| 5b | 20 | 7 | 1 | 3 | 0 | 250 |
| 5b | 19 | 6 | 7 | 3 | 0 | 300 |
| 6b | 10 | 1 | 3 | 4 | 300 | 100 |
| 6b | 18 | 1 | 0 | 4 | 240 | 300 |
| 7b | 1 | 3 | 4 | 6 | 0 | 0 |

## Appendix D. Main Script Code in BCE

```
 // Define Player List
                Players p1, p2;
                Integer nplayer = 2;
// Declare variables
                Script("c:\program files\hp mums\Scripts\buyback\var-model.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\var-dummy.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\var-state.cfg");
// Set parameter value
                Script("c:\program files\hp mums\Scripts\buyback\dat-parameter.dat");
// Define inputs
                Script("c:\program files\hp mums\Scripts\buyback\def-input.cfg");
// Stage logon
                Script("c:\program files\hp mums\Scripts\buyback\stage-logon.cfg");
// Game stages
                Script("c:\program files\hp mums\Scripts\buyback\stage-start.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-setgrid.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-predisplay.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-fetchdata.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-exchange.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-results.cfg");
                Script("c:\program files\hp mums\Scripts\buyback\stage-periodend.cfg");
//Creating  database log file
Stage writedb {
                     // no db write statements in debug
                     Script("c:\program files\hp mums\Scripts\buyback\stage-dblog-period.cfg");
                     if (stage=1)
                     {
                               End;
                     }
                     else
                     {
                               Goto start;
                     }
}
```

## Appendix E. The Script of dat-parameter.dat in BCE

```
stage setparameter
{
	if (period=1 & stage=1)
	{
	// parameters setting
		wholesalegiven = 0; //wholesale price is not given
		buybackgiven = 0;  // buyback price is not given

		value = 10;
		price = 6;
		searchcost = 2;
		wholesale = 0;
		buyback = 0;
		shippingcost = 100000;
		mindemand = 0;
		maxdemand = 1000;
		proximityfactor = 2;

	// manufacturer's stage description
		stagedesc[0,1] = "Wholesale and buyback price selection";
		stagedesc[0,2] = "Shipping time decision";
		stagedesc[0,3] = "Period results";

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

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

	if (stage = 1)
	{
	// assign match first
		matched = 0;
		pos = 0;
		for (i=0; i<nplayer; i=i+1)
		{
			allocation[i] = -1;
		}
		for (i=0; i<nplayer; i=i+1)
		{
			pos = int(nplayer*random);
			if (pos = nplayer)
			{
				pos = nplayer-1;
			}
			if (allocation[pos] = -1)
			{
				allocation[pos] = i;
			}
			else
			{
				while (allocation[pos] <> -1)
				{
					pos = (pos + 1) % nplayer;
				}
```

```
                        allocation[pos] = i;
                }
        }

        for (j=0; j<nplayer; j=j+2)
        {
                p1 = allocation[j];
                p2 = allocation[j+1];
                match[p1] = p2;
                match[p2] = p1;
                if ((lastrole[p1] < lastrole[p2]) | ((lastrole[p1] = lastrole[p2])& random <= 0.5))
                {
                        role[p1] = 0; // manufacturer
                        role[p2] = 1; // retailer
                        demand[p1] = mindemand + int((maxdemand - mindemand)*random);
                        demand[p2] = 0;
                        lastrole[p1] = lastrole[p1] + 1;
                }
                else
                {
                        role[p1] = 1; // retailer
                        role[p2] = 0; // manufacturer
                        demand[p1] = 0;
                        demand[p2] = mindemand + int((maxdemand - mindemand)*random
                        lastrole[p2] = lastrole[p2] + 1;
                }
        }

        if (wholesalegiven = 1  &  buybackgiven = 1) //wholesale  and buyback price are given
        {
                for (i=0; i<nplayer; i=i+1)
                {
                        if (role[i] = 0)
                        {
                                wholesaleset[i] = wholesale; //set given w
                                buybackset[i] = buyback; //set given b
                        }
                        else
                        {
                                wholesaleset[i] = -1; // w is not given
                                buybackset[i] = -1; // b is not given
                        }
                }
        }

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

## Appendix F. Instructions for Buyback Contract Experiments

### Scenario

We consider two independent firms: a manufacturer and a retailer. The manufacturer produces a product, which is sold to customers through two channels:

1) **The direct channel:** The manufacturer sells directly to customers through a web site.
2) **The retailer channel (or "the retailer" for short):** The retailer buys and stocks products from the manufacturer and sells them to customers in his physical store.

The two channels compete for customers. The total demand is distributed uniformly between 0 and 1000.

### Stages of the Game

**Stage I:** The manufacturer determines the following two contract terms:

- ***The wholesale price, w:*** The retailer pays this price to the manufacturer per product he orders. The wholesale price must be less than or equal to the given sales price $p$ of the product.
- ***The buyback price, b:*** This is the price the manufacturer pays to the retailer to buy back unsold products at retailer's store. The buyback price must be less than or equal to the wholesale price.

The retailer does not make any decision at this stage.

**Stage II:** Given the wholesale price and the buyback price decisions from stage I, at this stage, the firms make the following decisions:

- ***Stock quantity in the retailer channel, q***: The retailer determines how many products to order and stock from the manufacturer. Customers prefer higher stock quantity, because this increases product availability at the retailer's store. The stock quantity must be less than 1000, which is the maximum total demand.
- ***Shipping time in the direct channel, t:*** The manufacturer determines how fast the direct channel will ship products to customers. Customers prefer shorter shipping times. The shipping time must be at least 1.

These two decisions affect how the customers choose between the two channels. If the retailer's demand is less than its stock quantity, there will be unsold (leftover) units. The manufacturer buys back these units from the retailer by paying the buyback price per unit. If the retailer's demand is more than its stock quantity, the retailer loses customers. The direct channel, on the other hand, can satisfy all demand.

**<u>Retailer's Payoff</u>**

**Retailer's payoff** $= p * S_r \; - \; w * q \; + \; b*(q - S_r)$

- The first term denotes the retailer's sales revenue from customers (where $p$ is the sales price and $S_r$ is the retailer's sales quantity).
- The second term denotes the retailer's payment to the manufacturer for the products he bought.
- The third term denotes the manufacturer's buyback payment to the retailer for unsold products.

Retailer's sales quantity $S_r$ is a function of the retailer's stock quantity $q$ decision; manufacturer's shipping time t decision, and the realization of the random total demand. The retailer determines q without knowing t and the total demand realization. We do not provide the exact formula for the calculation *of* $S_r$.

***<u>Retailer's Trade-off</u>:***

Primarily, the retailer faces the standard "newsvendor" trade off:

- If the retailer's demand turns out to be lower than his stock quantity, some products will be unsold. The retailer loses money on unsold products because the buyback price that the manufacturer will pay to the retailer is less than or equal to the wholesale price.
- If the retailer's demand turns out to be higher than his stock quantity, he loses potential sales.

In addition to this, the stock quantity also affects the demand that the retailer faces. In general, a higher stock quantity means higher chances of finding the product in stock (that is, higher "product availability") for customers, which increases the share of total demand that goes to the retailer.

If the retailer stocks less than a certain quantity, no customer visits his store, because customers fear they will not be able to find the product available there. This "certain quantity" depends on the manufacturer's shipping time, which complicates the retailer's decision. At the extreme, if the manufacturer chooses a very short t, no customer visits the retailer even if he stocks very high quantity.

**Manufacturer's Payoff**

**Manufacturer Payoff** = $w * q + p * S_d - m/t^2 - b * (q - S_r)$

- The first term denotes manufacturer's revenue from selling q products to the retailer.
- The second term denotes the manufacturer's revenue from selling $S_d$ *products* in the direct channel.
- The third term denotes the cost of the direct channel, where parameter *m* is a given constant. Note that offering a shorter shipping time *t* becomes increasingly costly as *t* approaches 1.
- The fourth term denotes the manufacturer's payment to the retailer due to buying back his unsold products.

$S_d$ is a function of the manufacturer's *t* decision, retailer's *q* decision, and the realization of the random total demand. The manufacturer determines t without knowing *q* and the total demand. We do not provide the exact formula for the calculation of $S_d$. Note that the manufacturer does not incur a per unit production cost.

**Manufacturer's Trade-off**:

**Stage II decision:** When determining the shipping time *t:*

- A low *t* makes the direct channel more attractive to customers. The manufacturer earns more money when a product is sold in his direct channel than when it is sold through the retailer (because $p >= w$). However, the cost of the direct channel $m / t^2$ may become very high for short *t* values. In addition, if the retailer is left with many unsold products, the manufacturer may need to make him a high buyback payment (depending on the buyback price *b*).

- A high shipping time *t* costs less, but results in a weaker direct channel.

**Stage I decisions:** When determining the wholesale price *w* and buyback price *b:*

- If *w* is high, and *b* is low, it becomes risky for the retailer to buy products. The retailer may order and stock a low quantity, even zero products. This might leave the direct channel as the only strong alternative for customers. However, in this case, some customers may be lost because they would not buy from the direct channel unless the shipping time is sufficiently short.
- If *w* is low, and *b* is relatively high (it cannot exceed *w*), the retailer will probably order more products. However, the manufacturer will not make much money when selling to the retailer (due to low *w*), and may need to buy back unsold products at a high price (due to high *b*).

## Experiment Preparation

- The experiments will take place at the CAFÉ (Center for Applied Finance Education) computer lab at the G-floor of the FMAN building.
- Please come to the experiments on time so that we can start and finish on time.
- You will pass through a short quiz to make sure that you understand the rules of the experiment.
- 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 entry rules.

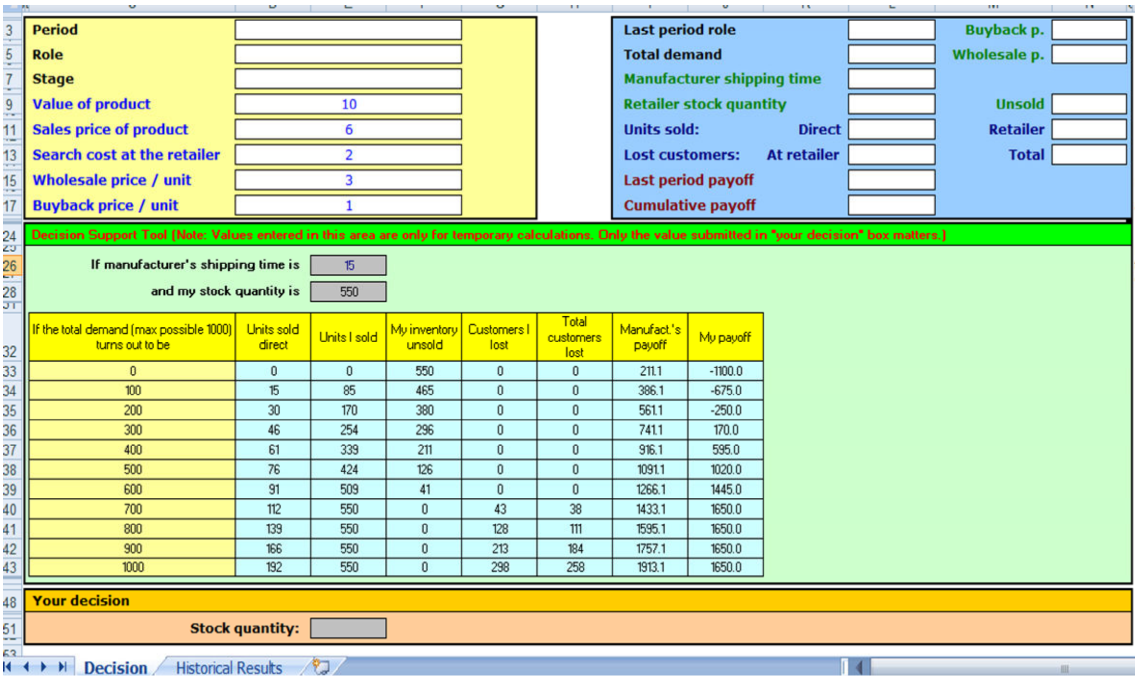
## The Experiment

- In the experiments, you will play the roles of manufacturer and retailer for a number of “periods”.
- The periods are independent of each other. For example, inventory is not carried from one period to the next. Only your payoff will accumulate over periods.

- In each period, the server computer will determine your role randomly. The server will also randomly match each manufacturer with a retailer. You will not know with whom you are matched.

## A Sample Screenshot

The following figure illustrates how the retailer's screen will look like at stage II:




| If the total demand (max possible 1000) turns out to be | Units sold direct | Units I sold | My inventory unsold | Customers I lost | Total customers lost | Manufact.'s payoff | My payoff |
|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 550 | 0 | 0 | 211.1 | -1100.0 |
| 100 | 15 | 85 | 465 | 0 | 0 | 386.1 | -675.0 |
| 200 | 30 | 170 | 380 | 0 | 0 | 561.1 | -250.0 |
| 300 | 46 | 254 | 296 | 0 | 0 | 741.1 | 170.0 |
| 400 | 61 | 339 | 211 | 0 | 0 | 916.1 | 595.0 |
| 500 | 76 | 424 | 126 | 0 | 0 | 1091.1 | 1020.0 |
| 600 | 91 | 509 | 41 | 0 | 0 | 1266.1 | 1445.0 |
| 700 | 112 | 550 | 0 | 43 | 38 | 1433.1 | 1650.0 |
| 800 | 139 | 550 | 0 | 128 | 111 | 1595.1 | 1650.0 |
| 900 | 166 | 550 | 0 | 213 | 184 | 1757.1 | 1650.0 |
| 1000 | 192 | 550 | 0 | 298 | 258 | 1913.1 | 1650.0 |

Figure 0.1. Sample Retailer Screen Shot

- The large table in the middle of the screen is your "**decision support tool**" (to be explained).
- The yellow box on the upper left presents general information including the period number, your current role, and the wholesale price and buyback prices that were set at stage I. The box also presents three game parameters that are given and fixed throughout all periods (value of product, sales price to customers, and the search cost). We use these parameters to characterize the business environment and product characteristics. You do not need to be concerned about their meaning. Their effect on how consumers choose between the channels is reflected in the decision support tool.

- The blue box in the upper right presents information on the last period. Not very important.
- The pink box in the bottom is where you "submit" your decision to the server. You enter your decision value into the related gray box, hit "enter" and then click on the green "Submit" button at the bottom (that will be visible during experiment). The submit button is activated only after you enter a valid decision and hit enter (or, click somewhere in the screen). Invalid entries will cause warnings.
- Note that the cells in which you can enter values are the ones with "gray" background.
- You can check the results of previous periods by clicking the "Historical Results" tab in the bottom. This will open a second worksheet with the titles seen below:

| | A | B | C | D | E | F | H | I | J | K | L | M | Q | R |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | | | | | |
| 2 | Period | Role | Wholesale price | Buyback price | Manuf. shipping time | Retailer stock quantity | Total demand | Units sold direct | Units sold by retailer | Units unsold by retailer | Customers lost at retailer | Total customers lost | Payoff | Cumulative payoff |
| 3 | | | | | | | | | | | | | | |
| 4 | | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | | |

Figure 0.2. Historical Results

## <u>The Decision Support Tool</u>

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

Pay attention to the decision support tool of the retailer for stage II, in the sample screenshot above. In the top two gray cells, you can enter a shipping time that you think the manufacturer may set, and a stock quantity that you may set.

- If this stock quantity is too low (for the customers to come to your store), a warning message will pop up (to the right of that blue box), prompting you to enter a higher stock quantity.

- If you enter a very short shipping time, the program will remind you that all customers will go to the direct channel if the manufacturer sets such a short shipping time.

To help you visualize the possible outcomes, the table in the decision support tool summarizes the outcome for 11 different total demand realizations (0, 100, 200… 1000), each in a row.

In the example above, the shipping time is entered as 15, and the retailer's stock quantity is entered as 550. We observe from the table that if total demand turns out to be, for example, 400, the manufacturer's direct channel will sell 61 units and you (retailer) will sell 339 units. You will be left with 550-339=211 units of inventory, which the manufacturer buys back. Since you satisfied all customer demand, you will not lose any customers. Also, all 400 customers will end up buying either from the direct channel or from you, hence total customers lost is also zero.

Compare this with the outcome if the total demand turns out to be 800. In this case, the direct channel will sell 139 units; you will sell all of your 550 units and you will lose 128 customers because you stocked-out. Out of these 128 customers you will lose, 111 will decide not to buy the product at all (because they find the shipping time in the direct channel long), whereas 128-111=17 will buy from the direct channel (which are among the direct channel's 139 customers). The last two columns provide your payoff and the manufacturer's payoff, which helps you guess the manufacturer's shipping time decision by experimenting with different combinations.

**Decision Support Tool (Note: values entered in this area are only for temporary calculations. Only the values submitted**

**If my shipping time is** 20, **wholesale price is** 3
, **buyback price is** 2
**and retailer's stock quantity is** 400,
**the cost of my direct channel would be** 250.00

| If total demand (maximum possible is 1000) turns out to be | Units I sold direct | Units sold at retailer | Total customers lost | My payoff | Retailer's payoff |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 150.0 | -400.0 |
| 100 | 14 | 86 | 0 | 406.0 | -56.0 |
| 200 | 27 | 173 | 0 | 658.0 | 292.0 |
| 300 | 41 | 259 | 0 | 914.0 | 636.0 |
| 400 | 54 | 346 | 0 | 1166.0 | 984.0 |
| 500 | 70 | 400 | 30 | 1370.0 | 1200.0 |
| 600 | 90 | 400 | 110 | 1490.0 | 1200.0 |
| 700 | 110 | 400 | 190 | 1610.0 | 1200.0 |
| 800 | 130 | 400 | 270 | 1730.0 | 1200.0 |
| 900 | 150 | 400 | 350 | 1850.0 | 1200.0 |
| 1000 | 170 | 400 | 430 | 1970.0 | 1200.0 |

**Your decisions**

**Wholesale price:** **Buyback price:**

Figure 0.3. Manufacturer's Decision Support Tool

If you are a manufacturer, your decision support tool at stage II will be somewhat similar to what we described for the retailer. At stage I, the manufacturer's decision support tool will look like above in the figure.

Because this is stage I, the decision support tool includes wholesale price and buyback price decisions. At this stage, you (the manufacturer) will only submit your wholesale price and the buyback price decisions. However, you may want to experiment with the stage II decisions (shipping time and stock quantity) as well. This is because you need to consider how the chosen wholesale price and buyback price will affect the stage II game between you and the retailer.

You can enter a shipping time that you may set and a stock quantity that you think the retailer may set at stage II. You can observe the resulting cost of your direct channel in the blue cell below these gray cells. If the stock quantity that you entered is too low, the program will remind you that the retailer is not likely to order such low quantity (because if he does so, no customer will visit his store).

## Appendix G. Outlier Data in Buyback Contract Experiments

Table 0.2. Outlier Data in Buyback Contract Experiments

| Exp. | Period | Manufacturer | Retailer | Wholesale Price | Buyback | Time to Ship | Stock Level |
|---|---|---|---|---|---|---|---|
| b1a | 8 | 4 | 6 | 2 | 5 | 20 | 350 |
| b1a | 28 | 3 | 2 | 5 | 5 | 300 | 1000 |
| b1a | 29 | 3 | 4 | 5 | 5 | 350 | 1000 |
| b1a | 17 | 8 | 2 | 5 | 2 | 400 | 300 |
| b1a | 19 | 3 | 4 | 5 | 5 | 500 | 350 |
| b1a | 20 | 3 | 2 | 5 | 5 | 1000 | 700 |
| b1a | 22 | 3 | 1 | 5 | 5 | 1000 | 800 |
| b1a | 24 | 3 | 1 | 5 | 5 | 1000 | 900 |
| b2a | 23 | 5 | 7 | 4 | 3 | 500 | 374 |
| b4a | 11 | 6 | 3 | 3 | 3 | 5000 | 1000 |
| b6a | 6 | 10 | 9 | 5 | 5 | 900 | 1000 |
| b6a | 28 | 1 | 5 | 5 | 4 | 800 | 600 |

## Appendix H. Relationship of Variables in Buyback Contract Experiments

Table 0.3. Relationship of Variables in Buyback Contract Experiments

| Exp. | Variables | | Relationship | $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|
| **b1a** | b | w | + | 0.24 | 0.00 | b = -1.709 + 0.892*w |
| | b | q | + | 0.25 | 0.00 | q = 240.806 + 73.848*b |
| | (w-b) | prom* | - | 0.14 | 0.00 | prom = 2178.646 - 254.723*(w-b) |
| | (w-b) | q | - | 0.53 | 0.00 | q = 685.019 -123.829*(w-b) |
| | w | q | - | 0.06 | 0.00 | q = 724.488 - 68.801*w |
| **b2a** | b | w | + | 0.14 | 0.00 | b = -0.094 + 0.525*w |
| | w | q | - | 0.12 | 0.00 | q = 839.813 - 110.561*w |
| | q | prom | + | 0.36 | 0.00 | prom = 497.425 + 2.578*q |
| **b3a** | t | q | + | 0.15 | 0.00 | q = 579.082 + 0.206*t |
| | b | q | + | 0.58 | 0.00 | q = 280.510 + 191.630*b |
| | b | t | + | 0.18 | 0.00 | t = -179.060 + 199.221*b |
| | (w-b) | q | - | 0.58 | 0.00 | q = -191.6*(w-b) + 855.4 |
| **b4a** | w | b | + | 0.18 | 0.00 | b = -0.378 + 0.474*w |
| | w | q | - | 0.24 | 0.00 | q = 819.792 -101.197*w |
| | q | prom | + | 0.17 | 0.00 | prom = 912.189 + 2.189*q |
| **b5a** | w | q | - | 0.20 | 0.00 | q = 1110.226 - 143.622*w |
| | b | q | + | 0.27 | 0.00 | q = 233.397 + 89.560*b |
| | (w-b) | q | - | 0.45 | 0.00 | q = 687.263 - 103.449*(w-b) |
| **b6a** | t | q | + | 0.20 | 0.00 | q = 444.641 + 2.877*t |
| | b | t | + | 0.18 | 0.00 | t = -41.761 + 21.181*b |
| | b | q | + | 0.40 | 0.00 | q = -301.011 + 208.605*b |
| | b | prom | + | 0.10 | 0.00 | prom = 207.504 + 423.649*b |
| | q | prom | + | 0.27 | 0.00 | prom = 792.580 + 2.076*q |
| | (w-b) | prom | - | 0.10 | 0.00 | prom = 2325.749 - 423.649*(w-b) |
| | (w-b) | q | - | 0.40 | 0.00 | q = 742.013 - 208.605*(w-b) |
| **b6b** | no relationship between parameters | | | | | |

* Manufacturer's profit

**Appendix I. Information on Multiple Linear Regression Analysis**

Multiple regression is a statistical method used to analyze the relationship between several independent variables (predictor variables) and a dependent variable (criterion variable). A dependent variable might have a relationship with a variable, more than one variable or none of the predictor variables. Analysis of variance (ANOVA) and multiple regression aim to explain the reason of the variance in the values of the dependent variable. Some of this variance is accounted for by the predictor variables that are identified. ANOVA shows the percentage of the variance that is accounted for by manipulation of the predictor variables. In multiple regression, we measure scores of the observed variables and try to identify which set of the observed variables predict the dependent variable best. In general, multiple regression procedures are used to estimate a linear equation of the form:

$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \ldots + \beta_p * X_p$ where
$Y$ is the dependent variable,
$X_1, X_2, \ldots, X_p$ are the predictor variables,
$\beta_0$ is the constant or intercept, and
$\beta_1, \beta_2, \ldots, \beta_p$ are the regression coefficients.

The following terms need to be understood to interpret the results of a multiple regression study:

Beta (Regression Coefficients): The beta is a coefficient of the predictor variable. The beta value shows how strongly each predictor variable affects the dependent variable. If the beta value is high for a predictor variable, the change in the value of this variable influences the dependent variable at a high level. If there is only one predictor variable in a model, the beta value is simply the correlation coefficient between the predictor and the dependent variable. If there are more than one predictor variable, the beta value of each predictor variable lets us to understand the contribution of each predictor variable to the model.

R, $R^2$, and Adjusted $R^2$: R is a correlation measure between the observed and the predicted value of the dependent variable. $R^2$ is the square of this measure and indicates the percentage in the variance of the dependent variable, which is explained by the model. This shows how good the prediction of the dependent variable can be made if we know the values of the predictor variables. However, $R^2$ might be overestimating the success of the model, because it can be artificially increased by adding predictor variables. Hence, another measure called "Adjusted $R^2$" is used. Adjusted $R^2$ takes into account the number of variables in the model and the number of the observations per each (Brace et al. 2006).

An important issue to consider while designing a multiple regression model is to choose predictor variables that are highly correlated with the dependent variable but not strongly correlated among themselves. When two or more predictor variables are strongly correlated, the condition called "multi-collinearity" occurs. If multi-collinearity exists, it is difficult to measure the contribution of each predictor variable to the success of the model. Hence, strongly correlated predictor variables should not be used in the model together.

Another important issue is the variable selection method. In order to measure the contribution of each predictor variable, one can use "simultaneous", "backward", "forward" or "stepwise" selection methods. In the "simultaneous" method (named as "enter" in SPSS), the set of the predictor variables are decided by the researchers and then the success of the model achieved by these variables is assessed. If one predictor variable is believed to be more important than others, "hierarchical" methods should be used. In such methods, the order or entrance of the variables into the model is specified according to some theoretical consideration or previous findings. When adding the variables to the model in an order, the contribution of each variable is assessed. If the predictive power of the model does not increase when a new variable is added, this variable is dropped.

In "statistical" methods, the correlation strength of predictor variables with the dependent variable is used to determine the order in adding (removing) the predictor variables to (from) the model. There are three different versions of this method, which are "forward" selection, "backward" selection and "stepwise" selection. In "forward" selection method, the predictor variables are entered to the model one by one according to strength of their correlation with the dependent variable. When a new variable is added, the change in the success of prediction is assessed. If the contribution is not significant, then this predictor variable is excluded. In the "backward" selection method, all predictor variables are entered to the model at the beginning. The predictor variables are removed according to the weakness of their correlation with the dependent variable. In each removal, the regression is re-calculated. If the prediction power of the model is decreased significantly, then this predictor variable is re-added to the model. Otherwise, this predictor variable is removed from the model. In the "stepwise" selection method, each predictor variable is entered to the model in a sequence. If adding a new variable increases the prediction power of the model, this variable stays in the model but all other variables in the model are re-tested. If an existing variable does not contribute to this new model anymore, it is deleted from the model. This method provides the smallest number of predictor variables in the model. In addition to these methods, SPSS provides a method called "remove" in which the variables are removed from the model in a block (Brace et al. 2006).

We used SPSS as the statistical tool to conduct multiple regression analysis. SPSS enters all predictor variables to the "first stage model" and calculates the partial correlation of each variable with the dependent variable given that all other predictor variables are in the model. Then, the program eliminates the variable which has the lowest partial correlation and jumps to the second stage model. After the elimination, the program recalculates the partial correlation of the variables which are in the second stage model and continues to do the same elimination until none of the variables can be eliminated and a final stage model is achieved. At each stage, the t and p-values of the predictor variables in the "coefficients" table show the impact of each predictor variable in the model on the dependent variable. A large absolute t and a small p-value indicate a large impact. At each stage, an F test is conducted and a p-value is calculated to test if the overall model at the given stage is significant or not. Using the F test, the significance of the overall model is tested with the below stated hypothesis:

$H_o$: $\beta_1=\beta_2=.........=\beta_7=\beta_8= \beta_9 =0$
$H_a$: At least one $\beta_i \neq 0$
<u>Decision Rule:</u> reject Ho at given significance level $\alpha = 0.1$ if $F^* > F_{\alpha,p-1,n-p}$ or p-value $\leq$ 0.1.

In SPSS, multi-collinearity is controlled by the tolerance measures. The tolerance values are the correlation values between the predictor variables and they can take values between 0 and 1. If a predictor's tolerance is close to zero, this predictor variable is strongly correlated with the other predictor variables. SPSS does not include a predictor variable in a model if its tolerance is less than 0.0001 (Brace et al. 2006). VIF is an alternative statistic to measure multi-collinearity, and a predictor variable should have a VIF value less than 10 to stay in the model.

## Appendix J. Subject-based Multiple Regression Analysis of Stock Level Decision

Table 0.4. Subject-based Regression Analysis of Stock Level Decision in Session 1

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1a | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | yes | demandt | 0.224 | 0.164 | 0.075 | stock =249.852 + 0.172*demandt |
| | 3 | no | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | yes | saler | 0.260 | 0.198 | 0.062 | stock = 273.804 + 0.304*saler |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | overage, demandt, saler | 0.717 | 0.623 | 0.008 | stock = 512.679 + 0.947*saler - 0.534*demandt - 0.635*overage |
| 1b | 0 | no | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | no | | | | | |
| | 4 | yes | overage | 0.368 | 0.297 | 0.048 | stock = 89.372 + 0.762*overage |
| | 5 | yes | lostrd | 0.304 | 0.235 | 0.063 | stock = 237.990 - 1.318*lostrd |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| | 8 | yes | stock, lostrd, overage | 0.695 | 0.581 | 0.018 | stock = 362.241 - 0.845*stock + 1.566*lostrd + 0.508*overage |
| | 9 | yes | stock | 0.469 | 0.415 | 0.014 | stock = 82.106 + 0.688*stock |
| 1c | 0 | Discarded | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | yes | demandt, overage | 0.532 | 0.415 | 0.048 | stock = -86.646 + 0.213*demandt + 0.537*overage |
| | 9 | no | | | | | |

Table 0.5. Subject-based Regression Analysis of Stock Level Decision in Session 2

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 2a | 0 | Discarded | | | | | |
| | 1 | yes | stock | 0.236 | 0.166 | 0.093 | stock = 662.477 - 0.469*stock |
| | 2 | yes | demandt | 0.217 | 0.151 | 0.094 | stock = 320.316 + 0.127*demandt |
| | 3 | Discarded | | | | | |
| | 4 | no | | | | | |
| | 5 | yes | stock, demandt, profitr | 0.775 | 0.714 | 0.001 | stock = 49.801 + 0.907*stock + 0.047*demandt - 0.03*profitr |
| | 6 | no | | | | | |
| | 7 | yes | saler, overage | 0.720 | 0.669 | 0.001 | stock = 45.404 + 1.043*saler + 0.462*overage |
| | 8 | Discarded | | | | | |
| | 9 | no | | | | | |
| 2b | 0 | no | | | | | |
| | 1 | yes | lostrd, demandt | 0.474 | 0.342 | 0.077 | stock = 486.112+0.433*lostrd - 0.175*demandt |
| | 2 | yes | stock, demandt, overage | 0.534 | 0.360 | 0.092 | stock = 117.993 + 0.458*stock + 0.118*demandt + 0.175*overage |
| | 3 | no | | | | | |
| | 4 | yes | stock | 0.805 | 0.786 | 0.000 | stock= -7.199 + 0.879*stock |
| | 5 | no | | | | | |
| | 6 | yes | stock, lostrd | 0.806 | 0.763 | 0.001 | stock = -2.270 + 1.069*stock - 0.493*lostrd |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | demandt, profitr | 0.556 | 0.445 | 0.039 | stock = 363.161 - 0.258*demandt + 0.094*profitr |
| 2c | 0 | Discarded | | | | | |
| | 1 | yes | saler, overage | 0.899 | 0.874 | 0.000 | stock = 41.290-4.394*saler + 0.825*overage |
| | 2 | Discarded | | | | | |
| | 3 | yes | saler | 0.978 | 0.976 | 0.000 | stock = 5.062 + 1.344*saler |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

Table 0.6. Subject-based Regression Analysis of Stock Level Decision in Session 3

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 3a | 0 | yes | overage, demandt | 0.455 | 0.318 | 0.088 | stock = 129.098 + demandt*0.619 + overage*0.816 |
| | 1 | yes | overage | 0.349 | 0.284 | 0.043 | stock = 444.707 - 0.441overage |
| | 2 | yes | stock, demandt, overage | 0.909 | 0.870 | 0.001 | stock = -60.805 + 0.267*stock + 0.629*demandt + 0.552*overage |
| | 3 | yes | overage | 0.395 | 0.327 | 0.038 | stock = 171.661 - 1.726*overage |
| | 4 | Discarded | | | | | |
| | 5 | yes | lostrd, stock, overage | 0.534 | 0.360 | 0.092 | stock = 173.156 + 0.735*stock - 0.383* lostrd - 0.253*overage |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| 3b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | no | | | | | |
| | 4 | yes | stock, overage, lostrd | 0.493 | 0.324 | 0.093 | stock = 249.203 - 0.383*lostrd + 0.459*stock - 0.218*overage |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| 3c | 0 | Discarded | | | | | |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | yes | profitr, saler | 0.768 | 0.717 | 0.001 | stock = -0.063 + 1.154*saler - 0.129*profitr |
| | 5 | Discarded | | | | | |
| | 6 | yes | lostrd | 0.356 | 0.291 | 0.041 | stock = 70.487 + 4.919*lostrd |
| | 7 | Discarded | | | | | |

Table 0.7. Subject-based Regression Analysis of Stock Level Decision in Session 4

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 4a | 0 | yes | wprice | 0.523 | 0.491 | 0.001 | stock = 673.032 - 133.026*wprice |
| | 1 | yes | wprice | 0.377 | 0.336 | 0.009 | stock = 653.659 - 65.041*wprice |
| | 2 | yes | wprice | 0.317 | 0.264 | 0.029 | stock = 473.216 - 61.701*wprice |
| | 3 | yes | wprice, stock, demandt | 0.866 | 0.832 | 0.000 | stock = 975.269 - 142.269*wprice - 0.234*prestock - 0.141*demandt |
| | 4 | no | | | | | |
| | 5 | yes | wprice | 0.640 | 0.615 | 0.000 | stock = 735.519 - 120.628*wprice |
| | 6 | yes | wprice | 0.513 | 0.478 | 0.002 | stock = 933.333 - 156.667*wprice |
| | 7 | yes | lostrd | 0.193 | 0.135 | 0.089 | stock = 460.427 - 0.289*lostrd |
| | 8 | yes | wprice | 0.865 | 0.856 | 0.000 | stock = 886.319 - 171.436*wprice |
| | 9 | yes | wprice | 0.506 | 0.473 | 0.001 | stock = 464.124 - 60.662*wprice |
| | 10 | yes | wprice | 0.185 | 0.126 | 0.097 | stock = 727.634 - 103.857*wprice |
| | 11 | yes | wprice, demandt | 0.399 | 0.314 | 0.028 | stock = 717.278 - 41.973*wprice - 0.237*demandt |
| | 12 | yes | wprice | 0.226 | 0.171 | 0.062 | stock = 876.839 - 144.323*wprice |
| | 13 | yes | wprice, lostrd | 0.820 | 0.795 | 0.000 | stock = 848.753 - 139.638*wprice + 0.331*lostrd |
| 4b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | yes | demandt | 0.397 | 0.346 | 0.016 | stock = 592.566 - 0.186*demandt |
| | 3 | no | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | yes | saler | 0.255 | 0.193 | 0.066 | stock = 377.423 - 0.480*saler |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | no | | | | | |
| | 10 | yes | demandt | 0.284 | 0.224 | 0.050 | stock=254.222 + 0.173*demandt |
| | 11 | yes | saler | 0.217 | 0.152 | 0.093 | stock = 510.729 - 0.352*saler |
| | 12 | yes | demandt | 0.290 | 0.231 | 0.047 | stock = 565.035 - 0.224*demandt |
| | 13 | yes | stock, profitr | 0.908 | 0.891 | 0.000 | stock = 48.249 + 0.871*prestock - 0.005*profitr |

Table 0.8. Subject-based Regression Analysis of Stock Level Decision in Session 5

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 5a | 0 | yes | wprice | 0.658 | 0.637 | 0.000 | stock = 901.333 - 217.333*wprice |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | yes | wprice | 0.962 | 0.960 | 0.000 | stock = 885.213 - 176.702*wprice |
| | 4 | no | | | | | |
| | 5 | yes | wprice | 0.209 | 0.156 | 0.065 | stock = 468.333 - 48.333*wprice |
| | 6 | no | | | | | |
| | 7 | yes | wprice, overage | 0.771 | 0.736 | 0.000 | stock = 1217.194 - 274.206*wprice + 0.196*overage |
| 5b | 0 | yes | saler | 0.373 | 0.320 | 0.020 | stock = 635.458 - 0.343*saler |
| | 1 | yes | overage | 0.258 | 0.191 | 0.076 | stock = 272.033 - 0.274*overage |
| | 2 | no | | | | | |
| | 3 | yes | demandt, overage | 0.741 | 0.689 | 0.001 | stock = 506.668 - 0.298*demandt + 0.147*overage |
| | 4 | yes | stock, saler | 0.834 | 0.803 | 0.000 | stock = 9.798 + 0.775*stock + 0.206*saler |
| | 5 | yes | profitr | 0.344 | 0.278 | 0.045 | stock = 518.502 - 0.095*profitr |
| | 6 | no | | | | | |
| | 7 | no | | | | | |

Table 0.9. Subject-based Regression Analysis of Stock Level Decision in Session 6

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 6a | 0 | yes | profitr, wprice, lostrd | 0.637 | 0.565 | 0.001 | stock = 561.723 - 0.061*profitr - 88.710*wprice + 0.646*lostrd |
| | 1 | yes | stock, wprice | 0.321 | 0.236 | 0.045 | stock = 480.262 + 0.563*prestock - 107.075*wprice |
| | 2 | yes | saler, profitr, wprice | 0.675 | 0.610 | 0.001 | stock = 644.224 + 0.834*saler - 0.152*profitr - 139.602*wprice |
| | 3 | yes | stock, wprice | 0.666 | 0.624 | 0.000 | stock = 448.128 + 0.606*prestock - 111.693*wprice |
| | 4 | yes | wprice | 0.337 | 0.298 | 0.009 | stock = 537.769 - 90.141*wprice |
| | 5 | yes | wprice | 0.371 | 0.334 | 0.006 | stock = 493 -104.333*wprice |
| | 6 | Discarded | | | | | |
| | 7 | yes | stock, wprice, demandt | 0.888 | 0.865 | 0.000 | stock = 918.142 + 0.163*stock - 0.131*demandt - 187.795*wprice |
| | 8 | yes | lostrd, wprice | 0.469 | 0.402 | 0.006 | stock = 609.726 - 1.888*lostrd - 115.683*wprice |
| | 9 | yes | wprice, lostrd | 0.769 | 0.740 | 0.000 | stock = 796.894 - 160.349*wpricesale - 5.346*lostrd |
| 6b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | no | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | no | | | | | |
| | 9 | Discarded | | | | | |

Table 0.10. Subject-based Regression Analysis of Stock Level Decision in Session 7

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 7a | 0 | yes | wprice | 0.484 | 0.447 | 0.003 | stock = 1154.875 - 192.167*wprice |
| | 1 | yes | wprice, stock, demandt, saler | 0.959 | 0.944 | 0.000 | stock = 1663.036 - 281.272*wprice - 0.385* stock - 0.141*demandt + 0.266*saler |
| | 2 | yes | wprice, saler | 0.478 | 0.398 | 0.015 | stock = 605.789 - 79.120*wprice + 0.377*saler |
| | 3 | yes | wprice | 0.627 | 0.603 | 0.000 | stock = 860.742 - 146.680*wprice |
| | 4 | yes | wprice | 0.565 | 0.536 | 0.001 | stock = 779.065 - 95.748*wprice |
| | 5 | yes | wprice, stock, saler | 0.626 | 0.540 | 0.004 | stock = 730.335 - 129.557*wprice - 0.505*stock + 0.705*saler |
| | 6 | yes | wprice | 0.920 | 0.914 | 0.000 | stock = 759.880 - 146.324*wprice |
| | 7 | yes | wprice | 0.688 | 0.667 | 0.000 | stock = 707.143 - 107.143*wprice |
| | 8 | yes | wprice | 0.744 | 0.726 | 0.000 | stock = 623.298 - 88.830*wprice |
| | 9 | yes | wprice | 0.670 | 0.648 | 0.000 | stock = 896.226 - 150.472*wprice |
| 7b | 0 | Discarded | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | no | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

## Appendix K. Subject-based Multiple Regression Analysis of Stock Level Decision with Dummy Variables

Table 0.11. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 1

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1a | 0 | yes | lostrd, overage | 0.426 | 0.321 | 0.047 | stock = 347.110 - 0.319*overage + 177.553*lostrd |
| | 1 | yes | lostrd, overage | 0.437 | 0.324 | 0.057 | stock = 328.490 - 0.101*overage+ 35.377*lostrd |
| | 2 | yes | demandt | 0.224 | 0.164 | 0.075 | stock = 249.852 + 0.172*demandt |
| | 3 | no | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | overage | 0.274 | 0.208 | 0.066 | stock = 479.515 - 0.360*overage |
| 1b | 0 | no | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | no | | | | | |
| | 4 | yes | overage | 0.368 | 0.297 | 0.048 | stock = 89.372 + 0.762*overage |
| | 5 | yes | overage, profitr, stock | 0.607 | 0.460 | 0.048 | stock = 215.362 - 1.122*stock + 358.031*profitr + 1.425*overage |
| | 6 | yes | stock, demandt, profitr, saler | 0.788 | 0.666 | 0.017 | stock = 228.077 + 0.589*stock - 0.062*demandt - 99.591*saler + 48.798*profitr |
| | 7 | no | | | | | |
| | 8 | yes | stock, lostrd, overage | 0.924 | 0.895 | 0.000 | stock = 778.742 - 0.874*stock - 435.813*lostrd + 0.611*overage |
| | 9 | yes | stock | 0.469 | 0.415 | 0.014 | stock = 82.106 + 0.688*stock |
| 1c | 0 | Discarded | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | yes | stock, demandt | 0.553 | 0.441 | 0.040 | stock = - 63.511 + 0.437*stock + 0.157*demandt |
| | 9 | no | | | | | |

Table 0.12. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 2

| **Exp.** | **Subject** | **Response** | **Response variables** | **$R^2$** | **Adj. $R^2$** | **p-value** | **Equation** |
|---|---|---|---|---|---|---|---|
| 2a | 0 | Discarded | | | | | |
| | 1 | yes | stock | 0.236 | 0.166 | 0.093 | stock = 662.477 - 0.469*stock |
| | 2 | yes | demandt | 0.217 | 0.151 | 0.094 | stock = 320.316 + 0.127*demandt |
| | 3 | Discarded | | | | | |
| | 4 | yes | lostrd, overage | 0.472 | 0.376 | 0.030 | stock = 198.797 + 459.383*lostrd - 0.838*overage |
| | 5 | yes | stock, profitr | 0.770 | 0.732 | 0.000 | stock = 92.857 + 0.857*stock - 50.000*profitr |
| | 6 | no | | | | | |
| | 7 | yes | stock | 0.498 | 0.456 | 0.005 | stock = 155.709 + 0.597*stock |
| | 8 | Discarded | | | | | |
| | 9 | yes | profitr, lostrd, overage | 0.580 | 0.465 | 0.019 | stock = 340.544 - 249.661*profitr + 316.052*lostrd - 1.102*overage |
| 2b | 0 | no | | | | | |
| | 1 | yes | saler, profitr | 0.560 | 0.450 | 0.037 | stock = 350.000 + 12.000*saler - 76.250*profitr |
| | 2 | yes | stock, saler, profitr | 0.892 | 0.852 | 0.000 | stock = 172.681 + 0.725*stock - 107.216*saler + 26.168*profitr |
| | 3 | no | | | | | |
| | 4 | yes | stock | 0.805 | 0.786 | 0.000 | stock = -7.199 + 0.879*stock |
| | 5 | no | | | | | |
| | 6 | yes | stock, overage | 0.756 | 0.701 | 0.002 | stock = -0.841 + 0.901*stock + 0.229*overage |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | overage | 0.287 | 0.208 | 0.090 | stock = 300.962 - 0.650*overage |
| 2c | 0 | Discarded | | | | | |
| | 1 | yes | stock | 0.565 | 0.516 | 0.008 | stock = 10.718 + 0.676*stock |
| | 2 | Discarded | | | | | |
| | 3 | yes | stock, saler, profitr, overage | 0.995 | 0.992 | 0.000 | stock = 0.830 + 1.182*stock + 70.522*saler - 55.064*profitr - 1.186*overage |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

Table 0.13. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 3

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 3a | 0 | yes | saler | 0.487 | 0.430 | 0.017 | stock = 305 + 322.778*saler |
| | 1 | yes | overage | 0.349 | 0.284 | 0.043 | stock = 444.707 - 0.441*overage |
| | 2 | yes | demandt, saler, overage | 0.926 | 0.894 | 0.000 | stock = -331.186 + 0.926 *demandt + 235.626*saler + 0.896*overage |
| | 3 | yes | lostrd | 0.476 | 0.418 | 0.019 | stock = 500 - 357.143*lostrd |
| | 4 | Discarded | | | | | |
| | 5 | yes | stock, profitr | 0.493 | 0.380 | 0.047 | stock = 75.689 + 0.665*stock + 101.575*profitr |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| 3b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | yes | saler | 0.481 | 0.429 | 0.012 | stock = 240 + 174.286*saler |
| | 3 | no | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | yes | saler | 0.231 | 0.161 | 0.096 | stock = 283.333 + 86.667*saler |
| 3c | 0 | Discarded | | | | | |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | yes | stock | 0.714 | 0.686 | 0.001 | stock = -5.36E-14 + 0.833*stock |
| | 5 | Discarded | | | | | |
| | 6 | no | | | | | |
| | 7 | Discarded | | | | | |

Table 0.14. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 4

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 4a | 0 | yes | wprice | 0.523 | 0.491 | 0.001 | stock = 673.032 - 133.026*wprice |
| | 1 | yes | wprice | 0.377 | 0.336 | 0.009 | stock = 653.659 - 65.041*wprice |
| | 2 | yes | wprice | 0.317 | 0.264 | 0.029 | stock = 473.216 - 61.701*wprice |
| | 3 | yes | wprice, stock, demandt | 0.866 | 0.832 | 0.000 | stock = 975.269 - 142.269*wprice -0.234*stock - 0.141*demandt |
| | 4 | no | | | | | |
| | 5 | yes | wprice | 0.640 | 0.615 | 0.000 | stock = 735.519 - 120.628*wprice |
| | 6 | yes | wprice | 0.513 | 0.478 | 0.002 | stock = 933.333 - 156.667*wprice |
| | 7 | no | | | | | |
| | 8 | yes | wprice | 0.865 | 0.856 | 0.000 | stock = 886.319 - 171.436*wprice |
| | 9 | yes | wprice | 0.506 | 0.473 | 0.001 | stock = 464.124 - 60.662*wprice |
| | 10 | yes | wprice, saler | 0.344 | 0.244 | 0.064 | stock = 488.571 - 103.857*wprice + 273.214*saler |
| | 11 | yes | wprice, demandt | 0.399 | 0.314 | 0.028 | stock = 717.278 - 41.973*wprice -0.237*demandt |
| | 12 | yes | saler, profitr | 0.395 | 0.302 | 0.038 | stock = 600 - 392.800*saler + 237.244*profitr |
| | 13 | yes | wprice, overage, profitr | 0.878 | 0.850 | 0.000 | stock = 968.669 - 137.276*wprice - 0.309*overage - 118.159*profitr |
| 4b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | yes | demandt | 0.397 | 0.346 | 0.016 | stock = 592.566 - 0.186*demandt |
| | 3 | no | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | no | | | | | |
| | 10 | yes | profitr | 0.338 | 0.283 | 0.029 | stock = 236.667 + 116.606*profitr |
| | 11 | no | | | | | |
| | 12 | yes | demandt | 0.290 | 0.231 | 0.047 | stock = 565.035 - 0.224*demandt |
| | 13 | yes | stock, profitr | 0.907 | 0.890 | 0.000 | stock = 46.698 + 0.897*stock - 11.079*profitr |

Table 0.15. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 5

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 5a | 0 | yes | wprice | 0.658 | 0.637 | 0.000 | stock = 901.333 - 217.333*wprice |
| | 1 | yes | wprice | 0.250 | 0.192 | 0.058 | stock = 788.393 - 113.393*wprice |
| | 2 | yes | wprice | 0.313 | 0.264 | 0.024 | stock = 644.000 - 99.333*wprice |
| | 3 | yes | wprice | 0.962 | 0.960 | 0.000 | stock = 885.213 - 176.702*wprice |
| | 4 | no | | | | | |
| | 5 | yes | wprice | 0.209 | 0.156 | 0.065 | stock = 468.333 - 48.333*wprice |
| | 6 | no | | | | | |
| | 7 | yes | wprice, stock, saler, overage | 0.851 | 0.797 | 0.000 | stock = 1380.234 - 341.446*wprice - 0.420*stock + 236.818*saler + 0.191*overage |
| 5b | 0 | yes | demandt | 0.359 | 0.305 | 0.024 | stock = 628.326 - 0.224*demandt |
| | 1 | yes | lostrd | 0.317 | 0.255 | 0.045 | stock = 355.455 - 180.455*lostrd |
| | 2 | no | | | | | |
| | 3 | yes | demandt, lostrd | 0.786 | 0.744 | 0.000 | stock = 479.914 - 0.330*demandt + 86.380*lostrd |
| | 4 | yes | stock | 0.765 | 0.746 | 0.000 | stock = 32.149 + 0.815*stock |
| | 5 | yes | profitr | 0.370 | 0.307 | 0.036 | stock = 777.000 - 368.636*profitr |
| | 6 | no | | | | | |
| | 7 | no | | | | | |

Table 0.16. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 6

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 6a | 0 | yes | stock, saler, wprice | 0.519 | 0.423 | 0.010 | stock = 608.175 - 0.726*stock + 267.464*saler - 109.392*wprice |
| | 1 | yes | wprice, overage | 0.263 | 0.170 | 0.087 | stock = 576.149 - 82.693*wprice + 0.339*overage |
| | 2 | yes | wprice | 0.502 | 0.473 | 0.001 | stock = 830 - 154*wprice |
| | 3 | yes | stock, wprice | 0.666 | 0.624 | 0.000 | stock = 448.128 + 0.606*stock - 111.693*wprice |
| | 4 | yes | wprice | 0.337 | 0.298 | 0.009 | stock = 537.769 - 90.141*wprice |
| | 5 | yes | wprice | 0.371 | 0.334 | 0.006 | stock = 493 - 104.333*wprice |
| | 6 | Discarded | | | | | |
| | 7 | yes | stock, wprice, demandt | 0.888 | 0.865 | 0.000 | stock = 918.142 + 0.163*stock - 0.131*demandt - 187.795*wprice |
| | 8 | yes | wprice, lostrd | 0.483 | 0.418 | 0.005 | stock = 385.498 - 101.083*wprice + 187.156*lostrd |
| | 9 | yes | demandt, profitr, wprice, lostrd | 0.757 | 0.687 | 0.000 | stock = 757.871 - 0.280*demandt + 175.956*profitr - 190.860*wprice + 156.903*lostrd |
| 6b | 0 | no | | | | | |
| | 1 | no | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | no | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | no | | | | | |
| | 9 | Discarded | | | | | |

Table 0.17. Subject-based Regression Analysis of Stock Level Decision with Dummy Variables in Session 7

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 7a | 0 | yes | wprice, profitr | 0.591 | 0.528 | 0.003 | stock = 868.447 - 162.789*wprice + 176.263*profitr |
| | 1 | yes | wprice, stock, saler | 0.960 | 0.950 | 0.000 | stock = 1513.254 - 306.627*wprice - 0.299*stock + 227.190*saler |
| | 2 | yes | wprice | 0.289 | 0.238 | 0.032 | stock=800 - 100*wprice |
| | 3 | yes | wprice | 0.627 | 0.603 | 0.000 | stock = 860.742 - 146.680*wprice |
| | 4 | yes | wprice | 0.565 | 0.536 | 0.001 | stock = 779.065 - 95.748*wprice |
| | 5 | yes | wprice | 0.401 | 0.361 | 0.006 | stock = 572.520 - 92.806*wprice |
| | 6 | yes | wprice | 0.920 | 0.914 | 0.000 | stock = 759.880 - 146.324*wprice |
| | 7 | yes | wprice | 0.688 | 0.667 | 0.000 | stock = 707.143 - 107.143*wprice |
| | 8 | yes | wprice, demandt, profitr, lostrd | 0.859 | 0.808 | 0.000 | stock = 485.980 - 67.750*wprice + 0.205*demandt - 62.526*profitr + 53.435*lostrd |
| | 9 | yes | wprice, profitr, lostrd, overage | 0.827 | 0.770 | 0.000 | stock = 891.658 - 151.066*wprice + 82.682*profitr - 109.182*lostrd + 0.150*overage |
| 7b | 0 | Discarded | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | yes | saler | 0.454 | 0.412 | 0.006 | stock = 100 - 85.286*saler |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

## Appendix L. Autocorrelation Analysis Results for Stock Level Decision

Table 0.18. Autocorrelation Analysis Results for Stock Level Decision

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 1a | 0 | -0.355 | -0.016 | 0.194 | 0.130 |
| | 1 | 0.114 | 0.326 | 0.081 | 0.637 |
| | 2 | -0.09 | -0.088 | 0.248 | 0.694 |
| | 3 | 0.128 | 0.145 | 0.003 | 0.584 |
| | 4 | 0.179 | -0.139 | -0.074 | 0.445 |
| | 5 | 0.304 | 0.251 | -0.043 | 0.195 |
| | 6 | 0.346 | 0.089 | 0.036 | 0.139 |
| | 7 | Discarded | | | |
| | 8 | 0.222 | 0.059 | -0.268 | 0.344 |
| | 9 | -0.005 | 0.171 | 0.178 | 0.982 |
| 1b | 0 | 0.298 | -0.013 | 0.027 | 0.229 |
| | 1 | 0.107 | -0.145 | -0.151 | 0.676 |
| | 2 | Discarded | | | |
| | 3 | -0.12 | -0.073 | 0.012 | 0.638 |
| | 4 | 0.152 | 0.336 | -0.324 | 0.551 |
| | 5 | -0.017 | 0.248 | 0.355 | 0.946 |
| | 6 | 0.397 | -0.073 | -0.226 | 0.109 |
| | 7 | 0.183 | 0.359 | 0.415 | 0.329 |
| | 8 | -0.149 | 0.068 | -0.067 | 0.419 |
| | 9 | 0.697 | 0.379 | 0.082 | 0 |
| 1c | 0 | Discarded | | | |
| | 1 | Discarded | | | |
| | 2 | Discarded | | | |
| | 3 | Discarded | | | |
| | 4 | Discarded | | | |
| | 5 | Discarded | | | |
| | 6 | Discarded | | | |
| | 7 | 0.068 | 0.468 | -0.049 | 0.785 |
| | 8 | 0.771 | 0.754 | 0.589 | 0 |
| | 9 | 0.384 | 0.231 | 0.092 | 0.038 |
| 2a | 0 | Discarded | | | |
| | 1 | -0.469 | 0.127 | -0.233 | 0.052 |
| | 2 | -0.210 | 0.025 | 0.068 | 0.380 |
| | 3 | Discarded | | | |
| | 4 | 0.015 | -0.107 | 0.149 | 0.950 |
| | 5 | 0.697 | 0.395 | 0.203 | 0.002 |
| | 6 | 0.259 | 0.308 | 0.144 | 0.268 |
| | 7 | 0.552 | 0.023 | -0.109 | 0.018 |
| | 8 | Discarded | | | |
| | 9 | 0.174 | -0.147 | -0.692 | 0.446 |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 2b | 0 | 0.357 | 0.453 | -0.066 | 0.162 |
| | 1 | 0.454 | 0.28 | 0.077 | 0.076 |
| | 2 | 0.52 | 0.364 | 0.103 | 0.036 |
| | 3 | -0.048 | -0.115 | -0.068 | 0.852 |
| | 4 | 0.8 | 0.538 | 0.354 | 0.001 |
| | 5 | 0.149 | 0.107 | 0.086 | 0.572 |
| | 6 | 0.725 | 0.444 | 0.164 | 0.003 |
| | 7 | -0.049 | -0.203 | -0.097 | 0.847 |
| | 8 | -0.197 | -0.047 | -0.032 | 0.428 |
| | 9 | 0.012 | -0.146 | -0.019 | 0.963 |
| 2c | 0 | Discarded | | | |
| | 1 | 0.64 | 0.373 | 0.132 | 0.012 |
| | 2 | Discarded | | | |
| | 3 | 0.61 | 0.287 | -0.1 | 0.014 |
| | 4 | Discarded | | | |
| | 5 | Discarded | | | |
| | 6 | Discarded | | | |
| | 7 | Discarded | | | |
| | 8 | Discarded | | | |
| | 9 | Discarded | | | |
| 3a | 0 | 0.498 | -0.037 | -0.089 | 0.052 |
| | 1 | 0.07 | 0.114 | -0.181 | 0.777 |
| | 2 | 0.146 | 0.027 | 0.03 | 0.569 |
| | 3 | 0.255 | -0.148 | -0.207 | 0.319 |
| | 4 | Discarded | | | |
| | 5 | 0.499 | 0.159 | -0.136 | 0.044 |
| | 6 | -0.174 | -0.174 | 0.43 | 0.497 |
| | 7 | 0.112 | -0.048 | 0.233 | 0.652 |
| 3b | 0 | -0.093 | 0.138 | 0.13 | 0.699 |
| | 1 | 0.007 | -0.057 | -0.071 | 0.978 |
| | 2 | 0.295 | -0.091 | -0.122 | 0.235 |
| | 3 | -0.188 | 0.629 | -0.143 | 0.436 |
| | 4 | 0.422 | 0.322 | 0.172 | 0.08 |
| | 5 | 0.199 | -0.304 | -0.331 | 0.409 |
| | 6 | -0.094 | -0.308 | -0.057 | 0.689 |
| | 7 | 0.224 | -0.09 | 0.004 | 0.353 |
| 3c | 0 | Discarded | | | |
| | 1 | 0.1 | 0.033 | -0.019 | 0.696 |
| | 2 | 0.077 | -0.199 | -0.011 | 0.757 |
| | 3 | Discarded | | | |
| | 4 | 0.767 | 0.535 | 0.302 | 0.002 |
| | 5 | Discarded | | | |
| | 6 | 0.235 | -0.176 | -0.047 | 0.343 |
| | 7 | Discarded | | | |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 4a | 0 | 0.108 | 0.23 | -0.044 | 0.62 |
| | 1 | 0.252 | -0.004 | 0.045 | 0.247 |
| | 2 | 0.025 | -0.264 | -0.417 | 0.914 |
| | 3 | -0.034 | 0.031 | -0.15 | 0.879 |
| | 4 | 0.179 | -0.41 | -0.26 | 0.411 |
| | 5 | -0.137 | -0.183 | -0.18 | 0.538 |
| | 6 | -0.136 | -0.022 | 0.047 | 0.541 |
| | 7 | 0.24 | -0.36 | -0.488 | 0.282 |
| | 8 | -0.54 | 0.221 | 0.033 | 0.013 |
| | 9 | -0.098 | -0.31 | -0.019 | 0.653 |
| | 10 | 0.127 | 0.034 | -0.33 | 0.569 |
| | 11 | 0.045 | 0.493 | 0.077 | 0.835 |
| | 12 | -0.288 | 0.187 | 0.055 | 0.196 |
| | 13 | -0.277 | -0.064 | 0.096 | 0.203 |
| 4b | 0 | 0.016 | -0.085 | -0.266 | 0.948 |
| | 1 | -0.153 | -0.297 | 0.092 | 0.514 |
| | 2 | 0.183 | -0.001 | -0.19 | 0.436 |
| | 3 | -0.033 | -0.185 | -0.096 | 0.888 |
| | 4 | 0.173 | 0.016 | 0.06 | 0.448 |
| | 5 | -0.109 | -0.146 | 0.046 | 0.661 |
| | 6 | -0.19 | -0.161 | 0.071 | 0.418 |
| | 7 | 0.387 | 0.025 | -0.05 | 0.108 |
| | 8 | 0.372 | -0.097 | -0.236 | 0.122 |
| | 9 | -0.267 | -0.178 | 0.187 | 0.254 |
| | 10 | 0.238 | 0.144 | -0.129 | 0.309 |
| | 11 | 0.104 | 0.07 | 0.021 | 0.658 |
| | 12 | -0.011 | 0.253 | -0.142 | 0.962 |
| | 13 | 0.741 | 0.46 | 0.334 | 0.002 |
| 5a | 0 | 0.336 | 0.129 | 0.005 | 0.268 |
| | 1 | 0.077 | -0.008 | -0.02 | 0.736 |
| | 2 | -0.087 | 0.037 | 0.066 | 0.697 |
| | 3 | 0.046 | 0.007 | 0.022 | 0.836 |
| | 4 | -0.133 | -0.308 | 0.139 | 0.542 |
| | 5 | -0.083 | -0.048 | 0.167 | 0.703 |
| | 6 | -0.153 | 0.09 | 0.203 | 0.493 |
| | 7 | 0.431 | -0.181 | -0.497 | 0.053 |
| 5b | 0 | -0.096 | 0.116 | -0.146 | 0.682 |
| | 1 | 0.047 | -0.262 | -0.188 | 0.847 |
| | 2 | 0.286 | 0.001 | -0.026 | 0.223 |
| | 3 | 0.415 | 0.283 | 0.309 | 0.085 |
| | 4 | 0.778 | 0.537 | 0.284 | 0.001 |
| | 5 | 0.187 | -0.189 | -0.292 | 0.452 |
| | 6 | 0.031 | 0 | -0.124 | 0.897 |
| | 7 | 0.203 | -0.357 | 0.22 | 0.399 |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 6a | 0 | -0.018 | -0.115 | -0.173 | 0.912 |
| | 1 | 0.284 | 0.032 | 0.202 | 0.087 |
| | 2 | 0.145 | -0.14 | -0.077 | 0.382 |
| | 3 | 0.596 | 0.589 | 0.36 | 0 |
| | 4 | 0.016 | 0.065 | -0.116 | 0.922 |
| | 5 | 0.165 | -0.062 | 0.055 | 0.32 |
| | 6 | Discarded | | | |
| | 7 | 0.202 | -0.27 | 0.032 | 0.225 |
| | 8 | -0.078 | 0.118 | -0.148 | 0.637 |
| | 9 | -0.236 | -0.192 | 0.112 | 0.156 |
| 6b | 0 | 0.469 | 0.492 | 0.229 | 0.012 |
| | 1 | 0.073 | 0.02 | 0.158 | 0.698 |
| | 2 | Discarded | | | |
| | 3 | Discarded | | | |
| | 4 | Discarded | | | |
| | 5 | Discarded | | | |
| | 6 | 0.22 | -0.119 | -0.267 | 0.241 |
| | 7 | Discarded | | | |
| | 8 | 0.106 | -0.222 | 0.073 | 0.668 |
| | 9 | Discarded | | | |
| 7a | 0 | 0.27 | 0.079 | 0.042 | 0.224 |
| | 1 | 0.013 | -0.333 | 0.151 | 0.953 |
| | 2 | 0.256 | 0.084 | 0.34 | 0.25 |
| | 3 | -0.029 | -0.177 | -0.169 | 0.895 |
| | 4 | -0.202 | -0.198 | 0.06 | 0.353 |
| | 5 | -0.233 | -0.037 | -0.01 | 0.284 |
| | 6 | 0.057 | -0.165 | -0.101 | 0.8 |
| | 7 | -0.001 | 0.079 | -0.002 | 0.995 |
| | 8 | 0.057 | -0.328 | -0.19 | 0.798 |
| | 9 | 0.372 | 0.238 | 0.062 | 0.087 |
| 7b | 0 | Discarded | | | |
| | 1 | Discarded | | | |
| | 2 | -0.212 | -0.057 | -0.127 | 0.353 |
| | 3 | Discarded | | | |
| | 4 | Discarded | | | |
| | 5 | Discarded | | | |
| | 6 | Discarded | | | |
| | 7 | Discarded | | | |
| | 8 | Discarded | | | |
| | 9 | Discarded | | | |

## Appendix M. Subject-based Multiple Regression Analysis of Delivery Lead Time Decision

Table 0.19. Subject-based Regression Analysis of Delivery Lead Time in Session 1

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 1a | 0 | yes | time, salem, profitm | 0.790 | 0.727 | 0.001 | time = 16.750 - 0.450*time - 0.023*salem + 0.004*profitm |
| | 1 | yes | time, salet | 0.381 | 0.268 | 0.072 | time = 3.885 + 0.630*time + 0.004*salet |
| | 2 | Discarded | | | | | |
| | 3 | yes | salem | 0.500 | 0.459 | 0.005 | time = 12.897 + 0.005*salem |
| | 4 | no | | | | | |
| | 5 | yes | demandt | 0.214 | 0.148 | 0.096 | time = 10.275 + 0.008*demandt |
| | 6 | yes | time | 0.473 | 0.429 | 0.007 | time = 5.575 + 0.715*time |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | no | | | | | |
| 1b | 0 | yes | time, salet, profitm | 0.579 | 0.398 | 0.093 | time = 57.904 + 0.008*profitm - 0.069*salet - 0.574*time |
| | 1 | Discarded | | | | | |
| | 2 | yes | time | 0.610 | 0.571 | 0.003 | time = 6.590 + 0.722*time |
| | 3 | yes | time | 0.343 | 0.277 | 0.045 | time = 11.467 + 0.503*time |
| | 4 | yes | demandt | 0.255 | 0.180 | 0.094 | time = 25.309 - 0.008*demandt |
| | 5 | yes | time | 0.353 | 0.273 | 0.070 | time = 8.697 + 0.586*time |
| | 6 | yes | demandt, salet, profitm | 0.891 | 0.844 | 0.001 | time = 27.004 + 0.004*profitm - 0.018*salet - 0.006*demandt |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | profitm | 0.357 | 0.286 | 0.052 | time = 58.003 - 0.007*profitm |
| 1c | 0 | Discarded | | | | | |
| | 1 | yes | time | 0.532 | 0.485 | 0.007 | time = 4.481 + 0.423*time |
| | 2 | Discarded | | | | | |
| | 3 | yes | time | 0.424 | 0.360 | 0.030 | time = 4.134 + 0.417*time |
| | 4 | yes | time | 0.801 | 0.779 | 0.000 | time = 1.414 + 0.856*time |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |
| | 8 | no | | | | | |
| | 9 | no | | | | | |

Table 0.20. Subject-based Regression Analysis of Delivery Lead Time in Session 2

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 2a | 0 | yes | time | 0.729 | 0.706 | 0.000 | time=2.653 + 0.823*time |
| | 1 | yes | salet, profitm | 0.356 | 0.239 | 0.089 | time = 13.488 - 0.010*salet + 0.002*profitm |
| | 2 | no | | | | | |
| | 3 | yes | salem | 0.251 | 0.194 | 0.057 | time = 18.566 - 0.014*salem |
| | 4 | yes | time | 0.800 | 0.784 | 0.000 | time = 2.972 + 1.052*time |
| | 5 | no | | | | | |
| | 6 | yes | time | 0.743 | 0.722 | 0.000 | time = 3.745 + 0.764*time |
| | 7 | no | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | yes | demandt | 0.247 | 0.178 | 0.084 | time = 12.986 + 0.003*demandt |
| 2b | 0 | Discarded | | | | | |
| | 1 | yes | time | 0.692 | 0.661 | 0.001 | time = 7.381 + 0.742*time |
| | 2 | yes | salem, demandt | 0.661 | 0.564 | 0.023 | time = 27.234 - 0.257*salem + 0.109*demandt |
| | 3 | no | | | | | |
| | 4 | yes | time | 0.550 | 0.500 | 0.009 | time = 10.164 + 0.893*time |
| | 5 | no | | | | | |
| | 6 | yes | time | 0.630 | 0.589 | 0.004 | time = 5.398 + 0.763*time |
| | 7 | yes | time, profitm, demandt | 0.690 | 0.534 | 0.057 | time = 23.506 + 0.474*time + 0.003*profitm - 0.023*demandt |
| | 8 | yes | demandt, salet | 0.693 | 0.616 | 0.009 | time = 24.247 + 0.042*demandt - 0.074*salet |
| | 9 | no | | | | | |
| 2c | 0 | Discarded | | | | | |
| | 1 | no | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | yes | time | 0.711 | 0.678 | 0.001 | time = 1.653 + 0.549*time |
| | 5 | Discarded | | | | | |
| | 6 | yes | time | 0.617 | 0.574 | 0.004 | time = 3.706 + 0.631*time |
| | 7 | Discarded | | | | | |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

Table 0.21. Subject-based Regression Analysis of Delivery Lead Time in Session 3

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 3a | 0 | yes | time | 0.620 | 0.582 | 0.002 | time = 4.351 + 0.786*time |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| 3b | 0 | yes | demandt | 0.234 | 0.165 | 0.094 | time = 93.617 - 0.105*demandt |
| | 1 | yes | time | 0.513 | 0.468 | 0.006 | time = 22.888 + time*0.482 |
| | 2 | no | | | | | |
| | 3 | yes | salem, demandt | 0.807 | 0.769 | 0.000 | time = 59.452 + 0.039*demandt - 0.467*salem |
| | 4 | yes | demandt | 0.270 | 0.203 | 0.069 | time = 23.050 - 0.007*demandt |
| | 5 | no | | | | | |
| | 6 | no | | | | | |
| | 7 | Discarded | | | | | |
| 3c | 0 | yes | profitm | 0.457 | 0.403 | 0.016 | time = 26.949 - 0.006*profitm |
| | 1 | yes | demandt | 0.263 | 0.190 | 0.088 | time = 38.791 - 0.028*demandt |
| | 2 | yes | time | 0.859 | 0.843 | 0.000 | time = 0.353 + 0.820*time |
| | 3 | yes | salem | 0.434 | 0.377 | 0.020 | time = 8.621 - 0.006*salem |
| | 4 | yes | demandt, salem | 0.750 | 0.688 | 0.004 | time = -1.291 + 0.050*demandt - 0.037*salem |
| | 5 | yes | time, demandt | 0.791 | 0.739 | 0.002 | time = 3.032 + 0.756*time - 0.003*demandt |
| | 6 | no | | | | | |
| | 7 | Discarded | | | | | |

Table 0.22. Subject-based Regression Analysis of Delivery Lead Time in Session 4

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 4a | 0 | yes | profitm, time, wprice | 0.881 | 0.852 | 0.000 | time = 2.1 + 3.352*wprice + 0.68*time - 0.003*profitm |
| | 1 | yes | demandt, salem | 0.787 | 0.755 | 0.000 | time = 27.813 + 0.018*demandt - 0.146*salem |
| | 2 | no | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | yes | time | 0.374 | 0.329 | 0.012 | time = 7.608 + 0.649*time |
| | 5 | no | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | no | | | | | |
| | 8 | yes | time, profitm | 0.353 | 0.253 | 0.059 | time = 14.899 + 0.404*time + 0.003*profitm |
| | 9 | yes | time | 0.345 | 0.298 | 0.017 | time = 13.704 + 0.587*time |
| | 10 | yes | demandt | 0.180 | 0.125 | 0.090 | time = 34.699 - 0.019*demandt |
| | 11 | yes | wprice | 0.224 | 0.169 | 0.064 | time = 20.673 + 4.264*wprice |
| | 12 | no | | | | | |
| | 13 | yes | time, profitm | 0.368 | 0.271 | 0.051 | time = 8.137 + 0.660*time - 0.002*profitm |
| 4b | 0 | no | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | yes | time, salem, salet | 0.654 | 0.539 | 0.018 | time = 55.979 - 0.605*time + 0.087*salem - 0.015*salet |
| | 4 | no | | | | | |
| | 5 | yes | demandt | 0.289 | 0.235 | 0.039 | time = 17.565 - 0.004*demandt |
| | 6 | no | | | | | |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | no | | | | | |
| | 10 | yes | salet | 0.252 | 0.184 | 0.080 | time = 44.736 - 0.036*salet |
| | 11 | no | | | | | |
| | 12 | no | | | | | |
| | 13 | Discarded | | | | | |

Table 0.23. Subject-based Regression Analysis of Delivery Lead Time in Session 5

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 5a | 0 | yes | time | 0.438 | 0.398 | 0.005 | time = 5.317 + 0.747*time |
| | 1 | yes | time, salem | 0.540 | 0.479 | 0.003 | time = 4.992 + 0.024*salem + 0.751*time |
| | 2 | no | | | | | |
| | 3 | no | | | | | |
| | 4 | yes | demandt, salem | 0.322 | 0.218 | 0.080 | time = 42.650 + 0.319*salem - 0.030*demandt |
| | 5 | no | | | | | |
| | 6 | yes | demandt, salet | 0.348 | 0.255 | 0.050 | time = 33.332 + 0.035*salet - 0.026*demandt |
| | 7 | no | | | | | |
| 5b | 0 | Discarded | | | | | |
| | 1 | no | | | | | |
| | 2 | no | | | | | |
| | 3 | no | | | | | |
| | 4 | yes | time, profitm | 0.566 | 0.488 | 0.010 | time = 3.691 + 1.126*time - 0.006*profitm |
| | 5 | yes | profitm | 0.260 | 0.198 | 0.063 | time = 19.806 + 0.002*profitm |
| | 6 | Discarded | | | | | |
| | 7 | Discarded | | | | | |

Table 0.24. Subject-based Regression Analysis of Delivery Lead Time in Session 6

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 6a | 0 | yes | wprice | 0.180 | 0.132 | 0.070 | time = 20.000 - 0.5*wprice |
| | 1 | yes | time, salem, salet | 0.715 | 0.658 | 0.000 | time=3.935 + 0.685*time - 0.006*salem + 0.004*salet |
| | 2 | Discarded | | | | | |
| | 3 | Discarded | | | | | |
| | 4 | yes | salet, profitm, wprice | 0.578 | 0.493 | 0.004 | time = 23.721 + 0.012*salet - 0.004*profitm - 0.964*wprice |
| | 5 | yes | salem, profitm | 0.262 | 0.169 | 0.088 | time = 18.904 - 0.017*salem + 0.002*profitm |
| | 6 | yes | profitm, wprice | 0.323 | 0.239 | 0.044 | time = 19.634 - 0.002*profitm + 1.212*wprice |
| | 7 | yes | time | 0.371 | 0.334 | 0.006 | time = 8.137 + 0.459*time |
| | 8 | yes | time | 0.315 | 0.274 | 0.012 | time = 9.979 + 0.415*time |
| | 9 | yes | profitm, salet, wprice | 0.557 | 0.468 | 0.006 | time = 16.482 - 0.004*profitm + 0.013*salet+ 1.561*wprice |
| 6b | 0 | yes | salem | 0.419 | 0.354 | 0.031 | time = 11.558 + 0.005*salem |
| | 1 | no | | | | | |
| | 2 | Discarded | | | | | |
| | 3 | yes | time, demandt, profitm | 0.702 | 0.574 | 0.030 | time = 32.231 - 0.980*time + 0.023*demandt - 0.006*profitm |
| | 4 | no | | | | | |
| | 5 | no | | | | | |
| | 6 | yes | salet | 0.429 | 0.372 | 0.021 | time = 20.305 - 0.005*salet |
| | 7 | no | | | | | |
| | 8 | no | | | | | |
| | 9 | yes | salem | 0.339 | 0.272 | 0.047 | time = 20.587 - 0.006*salem |

Table 0.25. Subject-based Regression Analysis of Delivery Lead Time in Session 7

| Exp. | Subject | Response | Response variables | $R^2$ | Adj. $R^2$ | p-value | Equation |
|---|---|---|---|---|---|---|---|
| 7a | 0 | no | | | | | |
| | 1 | Discarded | | | | | |
| | 2 | no | | | | | |
| | 3 | yes | wprice | 0.248 | 0.194 | 0.050 | time = 33.563 - 5.125*wprice |
| | 4 | no | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | yes | wprice | 0.462 | 0.426 | 0.003 | time = 38.000 - 5.000*wprice |
| | 7 | yes | wprice, time, demandt, salet, profitm | 0.879 | 0.818 | 0.000 | time = 10.362 - 1.895*wprice + 0.711*time + 0.012*demandt - 0.030*salet + 0.003*profitm |
| | 8 | Discarded | | | | | |
| | 9 | yes | wprice, time | 0.752 | 0.714 | 0.000 | time = 9.996 - 1.826*wprice + 0.775*time |
| 7b | 0 | Discarded | | | | | |
| | 1 | yes | salet | 0.430 | 0.383 | 0.011 | time = 7.288 - 0.005*salet |
| | 2 | yes | salem, time | 0.582 | 0.498 | 0.013 | time = 4.238 + 0.226*time - 0.002*salem |
| | 3 | Discarded | | | | | |
| | 4 | Discarded | | | | | |
| | 5 | Discarded | | | | | |
| | 6 | Discarded | | | | | |
| | 7 | yes | time | 0.776 | 0.757 | 0.000 | time = 1.061 + 0.781*time |
| | 8 | Discarded | | | | | |
| | 9 | Discarded | | | | | |

## Appendix N. Autocorrelation Analysis Results for Delivery Lead Time Decision

Table 0.26. Autocorrelation Analysis Results for Delivery Lead Time Decision

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 1a | 0 | -0.288 | 0.219 | 0.019 | 0.219 |
| | 1 | 0.34 | 0.379 | 0.093 | 0.146 |
| | 2 | Discarded | | | |
| | 3 | -0.113 | -0.085 | 0.125 | 0.571 |
| | 4 | 0.385 | 0.051 | 0.129 | 0.1 |
| | 5 | 0.121 | -0.168 | -0.131 | 0.604 |
| | 6 | 0.586 | 0.182 | 0.028 | 0.012 |
| | 7 | 0.085 | 0.068 | 0.05 | 0.723 |
| | 8 | 0.389 | 0.195 | 0.415 | 0.097 |
| | 9 | -0.029 | -0.186 | -0.231 | 0.898 |
| 1b | 0 | -0.032 | -0.141 | 0.186 | 0.9 |
| | 1 | Discarded | | | |
| | 2 | 0.722 | 0.218 | -0.282 | 0.004 |
| | 3 | 0.502 | 0.171 | 0.071 | 0.043 |
| | 4 | 0.281 | -0.032 | -0.211 | 0.257 |
| | 5 | 0.55 | 0.455 | 0.043 | 0.038 |
| | 6 | 0.113 | 0.312 | 0.046 | 0.659 |
| | 7 | 0.162 | -0.117 | -0.027 | 0.513 |
| | 8 | 0.356 | 0.207 | -0.002 | 0.164 |
| | 9 | 0.371 | -0.257 | -0.445 | 0.147 |
| 1c | 0 | 0.312 | 0.25 | 0.187 | 0.208 |
| | 1 | 0.39 | 0.306 | 0.222 | 0.115 |
| | 2 | Discarded | | | |
| | 3 | 0.41 | -0.181 | -0.174 | 0.109 |
| | 4 | 0.796 | 0.547 | 0.298 | 0.002 |
| | 5 | Discarded | | | |
| | 6 | Discarded | | | |
| | 7 | Discarded | | | |
| | 8 | 0.332 | -0.208 | -0.321 | 0.181 |
| | 9 | 0.116 | -0.229 | -0.303 | 0.651 |
| 2a | 0 | 0.788 | 0.546 | 0.364 | 0.001 |
| | 1 | 0.115 | 0.029 | 0.141 | 0.624 |
| | 2 | Discarded | | | |
| | 3 | 0.225 | 0.532 | 0.178 | 0.325 |
| | 4 | 0.693 | 0.43 | 0.256 | 0.003 |
| | 5 | 0.36 | 0.067 | 0.048 | 0.135 |
| | 6 | 0.687 | 0.474 | 0.256 | 0.003 |
| | 7 | -0.113 | 0.264 | -0.011 | 0.63 |
| | 8 | Discarded | | | |
| | 9 | -0.119 | -0.26 | 0.066 | 0.622 |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 2b | 0 | Discarded | | | |
| | 1 | 0.722 | 0.603 | 0.256 | 0.004 |
| | 2 | 0.258 | 0.039 | -0.073 | 0.329 |
| | 3 | 0.408 | 0.331 | 0.158 | 0.1 |
| | 4 | 0.554 | 0.319 | 0.212 | 0.031 |
| | 5 | 0.376 | -0.221 | -0.234 | 0.129 |
| | 6 | 0.641 | 0.225 | 0.136 | 0.012 |
| | 7 | 0.265 | 0.025 | -0.005 | 0.316 |
| | 8 | 0.577 | 0.281 | -0.068 | 0.024 |
| | 9 | 0.217 | 0.014 | -0.369 | 0.381 |
| 2c | 0 | Discarded | | | |
| | 1 | 0.313 | -0.32 | -0.116 | 0.207 |
| | 2 | Discarded | | | |
| | 3 | Discarded | | | |
| | 4 | 0.528 | 0.033 | -0.055 | 0.039 |
| | 5 | Discarded | | | |
| | 6 | 0.605 | 0.276 | 0.009 | 0.018 |
| | 7 | Discarded | | | |
| | 8 | Discarded | | | |
| | 9 | Discarded | | | |
| 3a | 0 | 0.757 | 0.475 | 0.156 | 0.002 |
| | 1 | 0.148 | 0.245 | -0.005 | 0.564 |
| | 2 | -0.003 | -0.197 | -0.435 | 0.991 |
| | 3 | Discarded | | | |
| | 4 | 0.299 | -0.267 | -0.336 | 0.229 |
| | 5 | 0.248 | 0.379 | 0.197 | 0.333 |
| | 6 | 0.015 | 0.1 | 0.224 | 0.951 |
| | 7 | -0.227 | 0.244 | 0.063 | 0.374 |
| 3b | 0 | 0.353 | -0.106 | -0.08 | 0.143 |
| | 1 | 0.471 | 0.246 | 0.23 | 0.051 |
| | 2 | 0.098 | -0.258 | -0.118 | 0.677 |
| | 3 | 0.682 | 0.364 | 0.282 | 0.005 |
| | 4 | -0.457 | 0.091 | -0.026 | 0.005 |
| | 5 | -0.316 | 0.317 | -0.302 | 0.189 |
| | 6 | -0.157 | 0.343 | 0.014 | 0.526 |
| | 7 | Discarded | | | |
| 3c | 0 | 0.576 | 0.11 | -0.15 | 0.02 |
| | 1 | 0.222 | 0.29 | 0.086 | 0.371 |
| | 2 | 0.668 | 0.445 | 0.269 | 0.009 |
| | 3 | 0.139 | 0.092 | 0.046 | 0.576 |
| | 4 | 0.538 | 0.282 | -0.044 | 0.035 |
| | 5 | 0.698 | 0.432 | 0.181 | 0.006 |
| | 6 | 0.316 | 0.399 | 0.155 | 0.216 |
| | 7 | Discarded | | | |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 4a | 0 | 0.75 | 0.521 | 0.273 | 0.001 |
| | 1 | 0.722 | 0.444 | 0.167 | 0.001 |
| | 2 | 0.285 | 0.061 | 0.173 | 0.189 |
| | 3 | Discarded | | | |
| | 4 | 0.57 | 0.381 | 0.067 | 0.01 |
| | 5 | -0.248 | -0.056 | -0.202 | 0.255 |
| | 6 | Discarded | | | |
| | 7 | -0.033 | 0.23 | 0.28 | 0.879 |
| | 8 | 0.22 | -0.088 | -0.169 | 0.324 |
| | 9 | 0.581 | 0.333 | 0.277 | 0.009 |
| | 10 | 0.079 | -0.346 | -0.168 | 0.716 |
| | 11 | -0.153 | -0.333 | 0.029 | 0.493 |
| | 12 | 0.267 | -0.219 | -0.288 | 0.219 |
| | 13 | 0.411 | 0.281 | 0.045 | 0.065 |
| 4b | 0 | 0.401 | 0.14 | 0.099 | 0.087 |
| | 1 | Discarded | | | |
| | 2 | Discarded | | | |
| | 3 | -0.535 | 0.297 | -0.042 | 0.026 |
| | 4 | 0.022 | -0.273 | -0.18 | 0.927 |
| | 5 | 0.49 | -0.105 | -0.434 | 0.032 |
| | 6 | -0.273 | 0.246 | -0.186 | 0.244 |
| | 7 | -0.186 | 0.047 | 0.415 | 0.426 |
| | 8 | -0.24 | -0.08 | 0.018 | 0.306 |
| | 9 | -0.248 | 0.265 | -0.257 | 0.29 |
| | 10 | 0.06 | -0.32 | -0.02 | 0.802 |
| | 11 | -0.006 | -0.127 | -0.061 | 0.981 |
| | 12 | 0.055 | -0.073 | -0.315 | 0.813 |
| | 13 | Discarded | | | |
| 5a | 0 | 0.587 | 0.338 | 0.327 | 0.008 |
| | 1 | 0.543 | 0.546 | 0.292 | 0.011 |
| | 2 | 0.003 | 0.094 | -0.045 | 0.99 |
| | 3 | -0.022 | -0.274 | -0.22 | 0.92 |
| | 4 | -0.195 | 0.143 | 0.238 | 0.381 |
| | 5 | 0.403 | 0.085 | -0.255 | 0.086 |
| | 6 | 0.426 | 0.241 | 0.222 | 0.05 |
| | 7 | -0.029 | 0.042 | 0.143 | 0.895 |
| 5b | 0 | Discarded | | | |
| | 1 | -0.122 | -0.471 | 0.068 | 0.603 |
| | 2 | 0.233 | 0.077 | -0.221 | 0.333 |
| | 3 | 0.123 | -0.209 | -0.376 | 0.6 |
| | 4 | 0.391 | 0.317 | -0.15 | 0.095 |
| | 5 | -0.198 | -0.479 | 0.243 | 0.398 |
| | 6 | Discarded | | | |
| | 7 | Discarded | | | |

| Exp. | Subject | Lag 1 | Lag 2 | Lag 3 | p-value |
|---|---|---|---|---|---|
| 6a | 0 | -0.227 | 0.141 | -0.046 | 0.275 |
| | 1 | 0.728 | 0.696 | 0.554 | 0 |
| | 2 | Discarded | | | |
| | 3 | Discarded | | | |
| | 4 | -0.071 | -0.216 | 0.248 | 0.731 |
| | 5 | 0.205 | -0.362 | -0.258 | 0.325 |
| | 6 | 0.224 | -0.012 | -0.067 | 0.28 |
| | 7 | Discarded | | | |
| | 8 | 0.39 | 0.126 | -0.04 | 0.061 |
| | 9 | -0.031 | -0.347 | -0.062 | 0.88 |
| 6b | 0 | 0.066 | -0.576 | 0.039 | 0.797 |
| | 1 | 0.033 | -0.105 | -0.146 | 0.901 |
| | 2 | Discarded | | | |
| | 3 | -0.205 | -0.29 | 0.258 | 0.423 |
| | 4 | 0.065 | -0.163 | 0.081 | 0.794 |
| | 5 | 0.104 | -0.187 | 0.207 | 0.675 |
| | 6 | 0.227 | 0.162 | -0.085 | 0.359 |
| | 7 | 0.158 | 0.23 | 0.005 | 0.537 |
| | 8 | -0.417 | -0.083 | 0 | 0.103 |
| | 9 | Discarded | | | |
| 7a | 0 | 0.25 | -0.208 | -0.329 | 0.103 |
| | 1 | Discarded | | | |
| | 2 | 0.216 | -0.124 | 0.028 | 0.321 |
| | 3 | 0.244 | -0.017 | -0.02 | 0.274 |
| | 4 | 0.182 | -0.034 | 0.038 | 0.414 |
| | 5 | Discarded | | | |
| | 6 | 0.134 | -0.047 | -0.016 | 0.538 |
| | 7 | 0.545 | 0.468 | 0.32 | 0.014 |
| | 8 | Discarded | | | |
| | 9 | 0.627 | 0.387 | 0.271 | 0.005 |
| 7b | 0 | Discarded | | | |
| | 1 | 0.123 | 0.073 | 0.104 | 0.599 |
| | 2 | 0.331 | -0.042 | 0.008 | 0.169 |
| | 3 | Discarded | | | |
| | 4 | Discarded | | | |
| | 5 | Discarded | | | |
| | 6 | Discarded | | | |
| | 7 | 0.74 | 0.353 | 0.135 | 0.002 |
| | 8 | Discarded | | | |
| | 9 | Discarded | | | |