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A Behavioral Study of Supply Chain Inventory Management

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A Behavioral Study of Supply Chain Inventory Management

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Abstract

This dissertation explores issues regarding inventory management in the domain of behavioral operations management by employing a combination of game theory analyses, human subject experiments, economic behavioral modeling, and numerical analyses. This dissertation consists of three chapters. The first chapter highlights the important role of strategic inventory in the multiperiod dual channel supply chain. The second chapter explores the effect of strategic disposal in the multiperiod Newsvendor supply chain. The last chapter further investigates the optimal strategy of strategic disposal and strategic carryover in the multiperiod supply chain with the present of supply disruption risk.

To my parents,

and my beloved wife.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1
INTRODUCTION

This dissertation explores issues regarding inventory management in the domain of behavioral operations management by employing a combination of game theory analyses, human subject experiments, economic behavioral modeling, and numerical analyses.

The first chapter highlights the important role of strategic inventory in the multiperiod dual channel supply chain. This study is the first to investigate, from a behavioral perspective, the impact of strategic inventory in a multiple period dual channels supply chain system. We focus on whether and how a retailer can use strategic inventory as a tool to regain some of the competitive advantage as the supplier can “squeeze” the retailer by offering the same products via her own, albeit less efficient, channel. To explore the strategic interaction between the supplier and the retailer, we employ a combination of game theory analyses, human subject experiments, economic behavioral modeling, and numerical analyses. We find that the retailer responds to inventory cost “more”, compared to the market power, and both the supplier’s and the retailer’s decisions deviated from the predictions of game theory due to individuals’ under-responding bias. Thus, we develop a structural model incorporating bounded rationality and fairness based on the quantal response equilibrium framework (QRE) to capture and measure the individual’s noisy decision-making behaviors.

The second chapter explores the effect of strategic disposal in a supply chain. Game theoretic analysis of a supplier-retailer system in a two-period newsvendor setting reveals that, on the part of the retailer, committing to disposal of inventory, that is to discard unsold inventory, rather than carryover to the next period, is preferred, under certain conditions, because of strategic reasons. In practice, strategic disposal is often being used when balancing between marginal cost and marginal revenue (i.e., Amazon warehouses in Britain and France trashed potentially millions of unsold products in 2019 because of its high inventory holding cost). Some may argue that strategic disposal may lead to waste, and it is not a good behavior to promote, because it has many negative impacts on the environment, economy, and society. We employ a combination of game theory, human-subject experiments, behavioral economics modeling, and numerical analyses to investigate the conundrum of inventory problems. In our model, the retailer has an option to make a commitment on whether to carry-over any surplus inventories or dispose of them at the end of period 1. Subsequent human subject experiments show that individuals choose inventory carryover more often in violation of game theoretic predictions. We identify past demand anchoring and overconfidence as the likely explanations amongst several alternatives and develop a behavioral model, based on the popular quantal response equilibrium framework, to explain the results.

The last chapter further investigates the optimal strategy of strategic disposal and strategic carryover in the multiperiod supply chain with the present of supply disruption risk. We study a two-period newsvendor setting in which the supplier is exposed under supply disruption risk and the retailer has the option either carryover or disposal of his inventory. We prove that in a special case in which the probability of supply disruption risk is equal to zero, the supplier will offer a lower weighted average wholesale price if the retailer commits to an inventory disposal strategy. Hence, a risk-neutral retailer will always choose to commit to inventory disposal to maximize his profit. However, as the probability of the supply disruption risk increases, the retailer will switch from inventory disposal strategy to the inventory carryover strategy. Relying on numerical analyses, we characterize how supply disruption risks change the strategic interactions between the supplier and the retailer.

Chapter 2

An Experimental Study of Strategic Inventory in Dual Channels

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2.1 Introduction

Inventory management has played an important role in the supply chain for several well-documented reasons (Zipkin 2000). The most common reason is that firms may carry inventories as a safety or buffer stock to hedge variation in the supply or the demand (Benjaafar et al. 2008, Corbett 2001). Other times, firms may take advantage of economic purchase order size, and hold their surplus as cycle inventory (Holt et al. 1960, Munson and Rosenblatt 1998). More importantly, inventory may be carried for strategic reasons. It is possible for a retailer to carry inventory as a strategic tool to influence a supplier's dominated power and force her to lower the wholesale price (Arya et al. 2014). Under certain thresholds, strategy inventory may alleviate the double marginalization problems between a supplier and a retailer, and lead to better channel performance in a non-competitive context (Anand et al. 2008, Roy et al. 2019). Based on the theoretical model by Anand et al. (2008), Hartwig et al. (2015) conduct laboratory experimental studies to examine the behavioral validity and reliability of the game theoretic predictions. They find empirical support for the effectiveness of using strategic inventory in a traditional vertical supply chain.

Although much attention was paid to the use of strategy inventory in vertical supply chains, in practice, most decentralized supply chain interactions take place in competitive settings. In particular, the advancement of internet technology and communication enable many companies to establish direct channels via e-commerce, often alongside their retail channel. Both the supplier's and the retailer's strategies will deviate from the traditional game theory predictions. To address this issue, we model a two-period dual channel supply chain, where the supplier not only sells to the retailer, but also sells the identical product directly to customers via her own market channel.

The core issue setting this line of inquiry apart from the existing, vertical supply chain focused, strategic inventory literature is that the supplier now has a way, the direct channel, to counteract the power of retailer's use of strategic inventory. We incorporate the nature of this new "power" of the supplier via a cost differential, referred to as the direct channel selling cost, between selling direct and selling through the retail channel. On one extreme, when there is no extra cost in selling directly, the supplier can eliminate the retailer, selling 100% directly, and disregard strategic inventory. On the other extreme, when selling directly is extremely expensive, the supplier will not use the direct channel and the setting reverts back to the classical vertical supply chain setting. On the side of the retailer, the power of strategic inventory is mitigated by the inventory holding cost. Thus, the tug of war between the power of the direct channel and the power of strategic inventory is driven by the direct channel selling cost of the supplier and the inventory holding cost of the retailer. This is the focus of this paper.

The key research question is whether the retailer's use of strategic inventory (i.e., how much inventory to hold) responds to the differential in power, driven by direct channel selling costs and inventory costs, as suggested by theory. There is, however, an important additional consideration. The original rationale of using strategic inventory is to reduce the retailer's future willingness to order (as he needs less inventory) and, hence, nudge the supplier to reduce the future wholesale price (Anand et al. 2008). The use of strategic inventory also depends on this rationale to be valid. With the addition of supplier-retailer competition, and a differential in market power, we need to determine if there is any change to the strategic consideration of how to set wholesale prices. That is, if and how much the future wholesale price would decrease as the inventory level increases.

To further complicate matters, human decision makers are known to deviate substantially from theory predictions (Schweitzer and Cachon 2000). As such, the behavioral perspective has gained substantial momentum in operations management research in recent years. In this study, we identify two potential behavioral issues. First, the role of strategic inventory, particularly in our setting where it is mitigated by differential market power, depends on strategic considerations, which can be sensitive to bounded rationality. Hence, we believe bounded rationality modifies how market power influences the use of strategic inventory. Secondly, the setting is multiple periods and while periods are mostly independent, with strategic inventory as the only link across time, events in previous periods, such as previous wholesale price and market price may act as anchors and introduce additional behavioral biases.

In this paper, we employ a combination of game theory analyses, human subject experiments, economic behavioral modeling, and numerical analyses. We consider a two-period setting with a standard dual channel structure where both the supplier and retailer compete in the same end market. Game theoretical analysis reveals that, in equilibrium, if the retailer carries strategy inventory, dependent on the setting parameters, the supplier will reduce the wholesale price in the second period in order to induce the retailer to order more, consistent with Anand et al. (2008) finding in a vertical supply chain with no supplier-retailer competition. We also show that when the retailer carries strategy inventory, the double marginalization problem is reduced, and the total supply chain performance is enhanced. Furthermore, we show that, in equilibrium, the retailer uses a threshold strategy of whether to use strategic inventory or not.

We conduct a series of controlled laboratory experiments to examine whether our game theory predictions align with human behavior. We find substantial underuse of strategic inventory in most treatments. In addition, we find retailers' responses to both market power and inventory cost changes lower than theory suggests. Moreover, they are less sensitive to market power than inventory costs. Similarly, suppliers have lower, compared to theory, responses to strategic inventory when they decide on wholesale price. All these results are consistent with bounded rational decision-makers.

We develop a behavioral model, incorporating bounded rationality and fairness by the use of the quantal response equilibrium framework (QRE) (McKelvey and Palfrey 1995), to explain these findings. We indeed verify that bounded rationality plays an important role in explaining the aforementioned behavioral anomalies. With numerical analyses, we further explore the implication of bounded rationality in this setting. This paper suggests that because of bounded rationality, strategic inventory is not as effective as suggested by theory. In addition, the supply chain seems to be more sensitive to the changes in inventory costs, compared to a "similar" change in market power.

This paper is organized as follows. In §2, we summarize the related theoretical and behavioral literature on strategic inventory, omnichannel distribution strategy in supply chain, and behavioral operations management. Section 3 provides the details of our models. Section 4 details our research hypotheses and the experimental design. The results are discussed in §5. Lastly, we conclude the paper with a discussion of the research and managerial implications, some limitations of this paper, and future extension of this work in §6.

2.2 Literature Review

Given our focus on the strategic inventory in dual channel, some important theoretical and experimental works exist, we provide a brief review of the relevant literature in the following three research areas: strategic inventory, omnichannel distribution strategy in supply chain, and behavioral operations management (BOM). In the end, we highlight key contributions in this paper.

The first area of research related to this paper is on strategic inventory. There has been extensive work in supply chain management about how strategic inventory could affect firms' profits in a vertical selling channel (Desaietal. 2010, Royetal. 2019). Anandetal. (2008) are among the first to recognize that strategic inventory plays an important role in terms of reducing double marginalization between the supplier and the retailer in a vertical supply chain. By carrying strategic inventory to hedge against upstream supply chain uncertainty, the retailer reduces the supplier's monopoly power on selling products, and forces the supplier to reduce the wholesale price in the later period, with the optimal effect to achieve a higher total supply chain efficiency. Hartwig et al. (2015) verify Anand et al. (2008) theoretical predictions by conducting controlled laboratory experiments. In their results, they talk about how inequality aversion and fairness might affect the different behaviors, but they did not describe any bounded rationality in terms of cost and power issues. In addition, Graves and Willems (2000) develop an optimization model to determine holding strategic inventory as safety stocks level at various nodes of a multistage supply chain. They demonstrate that holding strategic inventory could be the optimization solution for the company in a nonstationary demand market. Guan et al. (2019) develop and analyze two decentralized models of vertical competitions. They focus on the sequential quantity decisions with the first-mover advantage when the supplier has an option to encroach the market, and show that, under certain conditions, strategic inventory can benefit both the retailer and the supplier in a dual channel setting.

In this paper, we look at the theoretical predictions in the dual channel supply chain, where both the supplier and the retailer simultaneously make selling quantity decisions in each period. Then, we conduct human-subject experiments to investigate how strategic inventory affects the behavioral decisions where both the supplier and the retailer are bounded rational when dealing with different market power and holding cost issues.

Existing literature has investigated the optimal distribution strategy of an upstream supplier with limited/unlimited capacity (Chen et al. 2008, Chiang et al. 2003, Tsay and Agrawal 2004). The supplier's distribution decision may be divides into one of the three possible channels depending on the stochastic/deterministic market demand: monopolistic channel (sell via her direct channel only), dual channel (combination of a mix selling strategy), or independent channel (sell to downstream retailer only). There is a growing literature on dual channel management. According to a New York Times survey, more than 42% of top suppliers in wide range industries have begun to sell directly to consumers either online or offline (Tedeschi 2000). When the supplier using a dual channel strategy to compete with the downstream retailer, the competition can be modeled as price based (Tsay and Agrawal 2000), quantity based (Ha andTong2008), service based (Benjaafar et al. 2007), or location based (Alcacer and Chung 2007).

However, most research in this area is using a one-period model and assumes deterministic demand, which ignores the effects of strategic inventory. In this paper, for a better understanding about the effect of market power on strategic inventory, we assume the supplier could choose the dual channel strategy, and she has enough production capacity to fulfill all orders for identical products. The retailer, on the other hand, decides whether to carry strategic inventory during the multi-period stages.

Finally, this paper is also related to the literature on behavioral operations management (BOM). BOM has become a popular topic after Schweitzer and Cachon (2000) experimental paper, which describes how individuals do not solve problems correctly as game theory predicts. For example, Katok and Wu (2009) conduct laboratory experiments to investigate the effect of contracting in a vertical supply chain. Chen et al. (2008) study optimal dual channel strategies in service industries, which also state that humans are bounded rational when they want to maximize their profits but fail to do so, due to the limitations on their thinking capacity, available information, and time. When marking operation decisions, decision makers may be influenced by a number of behavioral tendencies, such as fail to judge risk (i.e., overconfidence and Bayesian updating), incorrect evaluation of outcomes (i.e., prospect theory and mental accounting), or bounded rationality (i.e., decision error and heuristics bias). In this paper, we examine how bounded rationality and fairness affect human decisions.

To the best of our knowledge, we are the first to use a series of laboratory experiments and behavioral models to explain the importance of carrying strategic inventory in a two-period dual channel setting, where the supplier decides her distribution strategy and the retailer decides his inventory strategy. Two recent works are closely related to this paper in terms of theoretical modeling and experimental design. Guan et al. (2019) focus on the sequential moves on selling quantity decisions, and the supplier can only encroach the market and compete in selling quantity with the retailer in period 2. Our model focuses on the retailer's profit change from period 1 to period 2 while carrying strategic inventory, and the supplier and the retailer independently and simultaneously make their selling decisions in both periods. Hartwig et al. (2015) strategic inventory in vertical supply chain experiments only required subjects to make wholesale prices and inventory quantity decisions. All other parameters or decisions are given either exogenous or automatically calculated by the computer given the best response formulas. In our experiments, all decisions are unrestricted, and the human subjects enter the input based on their own expectations. In addition, our laboratory experiment results not only validate the theoretical predictions and behavioral implications in our research hypotheses, but also point out some interesting phenomena about how people react differently on the market power and cost issues.

In our model, the supplier has enough production capacity to fulfill all orders, this assumption grants the supplier a superior competitive advantage, since she decides the wholesale price and direct selling quantity. In order to smooth the competition and apply to real-world industry, we assume when the supplier decides to use her direct selling channel, she pays a per unit selling cost. The selling cost could be viewed as the market power for the retailer. That the higher the market cost, the less the supplier will sell through her own channel, leading to less market competition. On the other hand, the retailer needs to pay a holding cost for every unit he decides to carry as the strategic inventory from period 1 to period 2. The implementation of how the supplier and the retailer make balance selling and inventory decisions when dealing with market power and holding cost issues in a multi-period dual channel supply chain drives the key insights in this paper.

2.3 Model Setting and Game Theoretical Prediction

We consider a two-period model in a dual channel supply chain setting, which consists of a retailer (he) and a supplier (she) with no capacity constraint. The supplier sells a product to the retailer, also directly sells the identical product to the end market. When the supplier sells via her direct channel, she pays a per unit selling cost. The retailer buys the product from the supplier at the wholesale price and resells it to the end market. The end market is modeled as a Cournot quantity competition with a linear price function, given by: $p(z_s,z_r) = d - a(z_s + z_r)$, where d is the maximum demand, a is the price sensitivity to quantity, and (z_s,z_r) are the selling quantities chosen by the supplier and retailer respectively. The retailer also chooses an inventory level, carried from period 1 to period 2, purchased at period 1 wholesale price, in addition to the two selling quantities decisions. We assume that d and α are strictly positive constants and are known to both the supplier and the retailer, common assumptions in the literature (e.g., Anand et al. 2008, Arya et al. 2007).

In addition to the strategic inventory setting, we also provide a “no-inventory” setting as a benchmark. In this setting, inventory is coerced to be zero and the retailer only determines selling quantities in each period. Since the two periods are completely independent, it can reduce to a one-period model.

The following table summarizes the sequences of events for the two settings (no inventory and strategic inventory).

Table 2.1. Game Sequence

	No-Inventory	Strategic Inventory
Stage 1	Supplier quotes wholesale price w_1	Supplier quotes wholesale price w_1
Stage 2	Retailer decides selling quantity z_{r1}. Simultaneously, supplier decides direct selling quantity z_{s1}	Retailer decides selling quantity z_{r1} and how much inventory to carry (I). Simultaneously, supplier decides direct selling quantity z_{s1}.

Stage 3	Supplier quotes wholesale price w_2	After observing retailer's inventory level (I), supplier quotes wholesale price w_2
Stage 4	Retailer decides selling quantity z_{r2}. Simultaneously, supplier decides the direct selling quantity z_{s2}	Retailer decides selling quantity z_{r2}. Simultaneously, supplier decides direct selling quantity z_{s2}

Market price function is identical in each period. Without loss of generality, we normalize both the supplier's production cost and the retailer's selling cost to zero. The supplier's direct selling cost c and the retailer's inventory holding cost h are the common knowledge.

The total profit for the supplier is:

$\Pi_s(w_1,z_{s1},w_2,z_{s2}) = (p_1 - c)z_{s1} + w_1(z_{r1} + max\,(I,0)) + (p_2 - c)z_{s2} + w_2(z_{r2} - max\,(I,0))$

The total profit for the retailer is:

$\Pi_r(z_{r1},I,z_{r2}) = p_1 z_{r1} - w_1(z_{r1} + max\,(I,0)) - max\,(I,0)h + p_2 z_{r2} - w_2(z_{r2} - max\,(I,0))$

where $p_t(z_{st},z_{rt}) = d - a(z_{st} + z_{rt})$, period $t = 1,2$.

2.3.1 Theoretical Analysis

We characterize the subgame-perfect Nash equilibriums of the game under the "no inventory" and the "strategic inventory" settings, and summarize the results in Table 1. Please see Appendix A for full results.

As mentioned before, we operationalize the differential in market power by including a *direct channel selling cost c* on the part of the supplier. When c is low, the supplier can eliminate the retailer, selling 100% direct, and disregard strategic inventory. On the other extreme, when c is high, the supplier will not use the direct channel and the setting reverts back to the classical vertical supply chain setting. Both extreme cases have been covered in previous literatures (Anand et al. 2008, Arya et al. 2014, Guan et al. 2019). Hence, we focus our attention on the range of c ($0 < c < 5d/7$) where the supplier will use both his own channel and the retail channel. On the retailer side, the power of strategic inventory is mitigated by the inventory holding cost h.

	No-Inventory Model	Strategic Inventory Model
Wholesale price $\{w_1, w_2\}$	$\{\frac{5d-c}{10}, \frac{5d-c}{10}\}$	$\{\frac{355d-50h-47c}{710}, \frac{71d+110h-67c}{142}\}$
Supplier selling $\{z_{s1}, z_{s2}\}$	$\{\frac{5d-7c}{10\alpha}, \frac{5d-7c}{10\alpha}\}$	$\{\frac{1065d-50h-1467c}{2130\alpha}, \frac{213d+110h-351c}{426\alpha}\}$
Retailer order $\{r_{o1}, r_{o2}\}$	$\{\frac{2c}{5\alpha}, \frac{2c}{5\alpha}\}$	$\{\frac{2526c-2600h}{3195\alpha}, \frac{150c+220h}{639\alpha}\}$
Retailer selling $\{z_{r1}, z_{r2}\}$	$\{\frac{2c}{5\alpha}, \frac{2c}{5\alpha}\}$	$\{\frac{402c+50h}{1065\alpha}, \frac{138c-110h}{213\alpha}\}$
Inventory I	0	$\frac{264c-550h}{639\alpha}$

2.3.2 Strategic Inventory

In this section, we discuss the main game theoretic modeling results.

Proposition 1: Retailer carries strategic inventory for $h \leq 0.48c$**.**

Proof: Please see appendix B.

The first proposition captures the main trade-off of the setting. Strategic inventory (I) is increasing in c and decreasing in h. When c is higher, the supplier's direct channel is less efficient, and the supplier has to rely on the retailer channel more, which increases the market power of the retailer. As a result, the retailer has more "room" to use strategic inventory (i.e., higher I). On the other hand, a higher holding cost pushes the retailer to use less strategic inventory.

This result is consistent with Anand et al. (2008), which uses a vertically integrated supply chain setting. In their setting, strategic inventory has a linear decreasing relationship with its holding cost, where $I = (5d - 20h)/34a$. In the dual channel setting here, strategic inventory also has a decreasing linear relationship with the holding cost. However, compared with the single channel, the inventory responses to the holding cost is stronger (a more negative coefficient) in the dual channel case reflecting the weaker marketing power, and hence less advantage from the use of strategic inventory, of the retailer because the supplier can shift sales to its own channel.

2.3.3 Second Period Wholesale Price Response to Inventory

Result 1: Wholesale price in period 2 (w2) is decreasing in strategic inventory: $w_2 = 1/10(-c + 5d - 9\alpha I)$

This result captures the effect of strategy inventory on the supplier's wholesale price in period 2. When carrying inventory from period 1, the retailer tends to order less from the supplier in period 2 because the size of the market demand is remaining unchanged. Hence, the supplier will reduce her wholesale price in order to induce the retailer to order more.

Result 2: Weighted average wholesale price is lower in the strategic inventory model than the no-inventory model.

Proof: Please see Appendix B.

From the theoretical predictions in section 3.1 we observe that period 1 (respectively, period 2) wholesale price under the strategic inventory model is larger (respectively, smaller) than the wholesale price in the no-inventory model. To compare the wholesale price over the two-period setting, we consider a weighted average wholesale price, where the weight is the retailer's ordering quantities. It is straightforward to show that the weighted average wholesale price is lower in the strategic inventory model compared with no-inventory model. Intuitively, one would expect a lower overall wholesale price may be able to reduce the impact of double marginalization and to increase supply chain efficiency. However, it turns out that the situation is not as straightforward. The next proposition addresses how strategic inventory impacts supply chain efficiencies.

2.3.4 Strategic Inventory May Enhance Supply Chain Efficiency

We define supply chain efficiency as the sum of all players' profits.

Proposition 2: Supply chain efficiency is higher in the strategic inventory model than the no-inventory model, $\Pi_{SC}^{I} \geq \Pi_{SC}^{NI}$ **for** $h \leq \frac{649}{1500}c \approx 0.43c$

Proof: Please see Appendix B.

Note that as long as $h \leq 0.48c$, the retailer should carry inventory (Proposition 1). However, the supply chain efficiency is higher in the strategic inventory model than that of the no-inventory model only when $h \leq \frac{649}{1500}c \approx 0.43c$. Hence, strategic inventory results in a LOWER total supply chain efficiency when $0.43c < h \leq 0.48c$. In this case, the overall decrease in average wholesale price, across two periods weighted by quantity, does not help to increase the total supply chain efficiency.

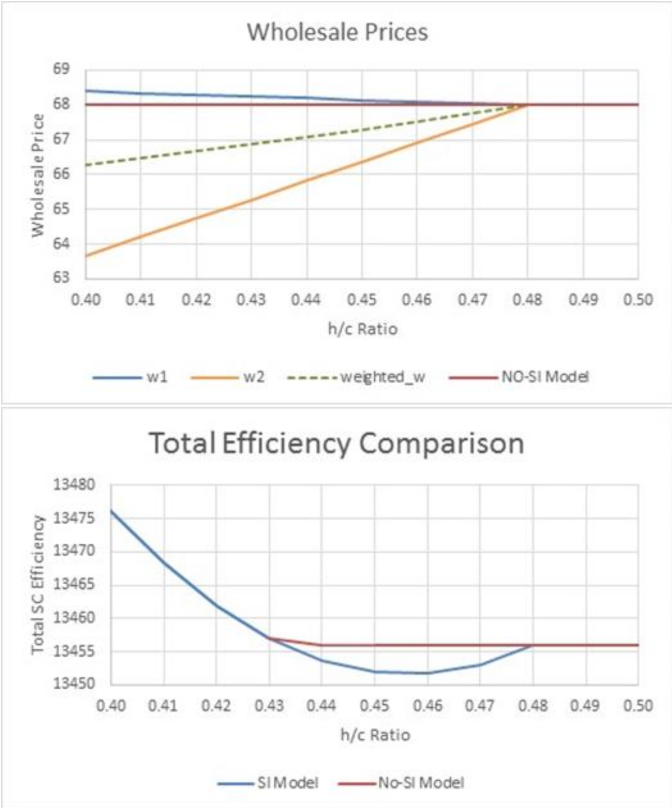


Figure 2.1. Predictions

2.4 Research Hypotheses and Experimental Design

Game theory assumes perfect rationality and a growing literature suggests human decision-making behaviors in operations settings can deviate substantially (Chen et al. 2008, Katok and Wu 2009, Schweitzer and Cachon 2000). We design a series of human subject experiments to stress-test the conclusions of the analysis reported in section 3. To help clarify intent of the experimental design and calibration, we adapt the analytical results into testable hypotheses.

2.4.1 Research Hypotheses

The first three hypotheses are motivated by proposition 1 and cover the central issue of the paper: when and how strategic inventory should be used. Proposition 1 has three main components. First, the retailer should carry inventory if and only if the inventory carry cost (h) is lower than a particular threshold. Hence:

Hypothesis 1. (Inventory Threshold)

(1a) Retailer carries strategy inventory when $h \leq 0.48c$.

(1b) Retailer does not carry strategy inventory when $h > 0.48c$.

Second, when the supplier marketing cost/retailer market power c is higher, inventory should increase. Hence:

Hypothesis 2. (Strategic Inventory Increases with *c*) Strategic inventory is increasing in market power c.

Third, when the retailer's inventory cost h is higher, inventory decreases.

Hypothesis 3. (Strategic Inventory Decreases with *h*) Strategic inventory is decreasing with its holding cost h.

The last two hypotheses address the issue of overall supply chain performances. Result 2 states that the second period wholesale price is decreasing in inventory.

Hypothesis 4. (Coordination on Wholesale Price) The wholesale price in period 2 is decreasing in inventory.

The last hypothesis captures how supply chain efficiency responses to the parameter changes in the setting, illustrated by Figure 1. In particular, when the inventory holding cost is lower than the threshold $0.43c$, the total supply chain profits increase if inventory is allowed. When inventory holding cost is between $0.43c$ and $0.48c$, the total supply chain profits decrease if inventory is allowed. If the holding cost is higher than $0.48c$, there will be no inventory even if inventory is allowed. Thus, we omit the last case. Hence:

Hypothesis 5 (Supply Chain Efficiency)

(5a) Total supply chain efficiency is higher in the strategic model than no-inventory setting when $h < 0.43c$.

(5b) Total supply chain efficiency is lower in the strategic model than no-inventory setting when $0.43c < h \leq 0.48c$.

2.4.2 Experimental Design and Calibration

The design of the experiments focuses on two key variables, the supplier marketing cost and the retailer inventory holding costs. We use a standard 2×2 between-subjects full factorial design for a total of four treatments. Table 2 summarizes the experimental design, predicted inventory level, and sample sizes. Each treatment is labeled as H_iC_j with $i,j \in \{L,H\}$: $H_L(H_H)$ representing the retailer's low (high) holding cost; $C_L(C_H)$ represents the supplier's low (high) direct selling cost, in other words, the retailer's low (high) market power.

Table 2.2. Experimental Design and Number of Participating Subjects

Treatment	Predicted Inventory Level	Sample Size	No. of rounds	No. of data points
(a) H_LC_L	23	292	1	146
(b) H_HC_L	0	300	1	150
(c) H_LC_H	56	294	1	147
(d) H_HC_H	23	290	1	145

Notes. 1. In all treatments, w_t,z_{st},z_{rt},q_t,I = [0,150] and t = 1,2.

2. $H_i(C_i)$ with $i = L$ or H represents a low or a high inventory holding (direct selling) cost.

We calibrate the parameters so that the H_HC_L treatment, used as a baseline, has an inventory holding cost higher than the threshold of 0.48c and hence the retailer should not hold inventory. We created two treatments H_LC_L and H_HC_H, by lowering the inventory holding cost and increasing the supplier marketing cost respectively, so that the threshold condition for inventory use would be met. The intent is to test hypothesis 1 two ways, and to see if we can enable strategic inventory use by either making holding inventory cheap enough or the threshold (based on supplier's market cost) high enough.

We also intentionally calibrate the H_LC_L and H_HC_H treatments so that the inventory level of the two are the same under the Nash equilibrium. The goal is to determine if game theory accounts for the strategic forces that push inventory up and down correctly.

Finally, we include a treatment, H_LC_H, where the inventory use would increase, compared to H_LC_L and H_HC_H, because either the retailer holding cost is decreased or the supplier marketing cost is increased. This enables us to test hypothesis 2 and 3.

There are obviously infinite sets of parameters we can use in the experiments. We arbitrarily set the price intercept $d = 150$, and the market sensitive factor $\alpha = 0.5$, so the inverse market price function becomes $p_t(z_{st},z_{rt}) = 150 - 0.5(z_{st} + z_{rt})$ in all four treatments. We pick $H_L(H_H) = 1(20)$, and $C_L(C_H) = 30(70)$ as the treatment variation to satisfy the model conditions while giving enough room to the subjects to have a clear incentive. All input decisions for both the supplier and the retailer are bounded, meaning that $w_t,z_{st},z_{rt},q_t,I = [0,150]$ and $t = 1,2$, to isolate unreasonable results. The main goal of this paper is to study the interaction of strategic inventory carry behavior and period 2 wholesale price fluctuation in the dual channel supply chain.

2.4.3 Experimental Procedures

At the beginning of each treatment, the participants were given instructions, quiz questions, and practice rounds to ensure that they understood the task. Only if a participant correctly passed the quiz questions could (s)he start the practice rounds and continue to the real experiment. To minimize the mathematical error, an embedded decision support tool was provided on participants' screens to facilitate them to make decisions. Specifically, when making an order or selling decision, both the supplier and the retailer had the ability to enter hypothetical orders or selling quantities for both parties and observe the potential profits for themselves and the other party (screenshots are provided in Appendix C). After successfully passing 2 quiz questions, the participants first played both the retailer and the supplier roles separately against the computer for 2 decision periods. The purpose of the practice rounds was to ensure that complexity was not a drive of any results. We wanted the participants to fully understand how to play the game by playing both roles. Finally, the participants were randomly assigned to be either the supplier or the retailer after they entered the real interaction game with a random partner.

On average, we have 294 participants randomly paired up and played for 1 round (2 decision periods) in every treatment. Since this is a true one-shot experiment, we gathered 147 data points, which has neither learning nor timing effect, in each treatment.

2.4.4 Amazon Mechanical Turk (MTurk) Protocol

The experiments were organized on Amazon Mechanical Turk (MTurk) using the Software Platform for Human Interaction Experiments (SoPHIE) (https://www.sophielabs.com) with standard experimental economics methodology and use no deception. SoPHIE is a web-based platform to run real-time interaction experiments. It has a built-in function that integrates with MTurk's Application Programming Interface (API), which allows us to monitor the participants' real-time actions.

There have been multiple studies examining questions about why researchers should use MTurk and how valid its data results are. The conclusions have been mostly favorable about conducting experiments via MTurk since the data collected from MTurk appears as valid as data collected from other sources (Buhrmester et al. 2011, Paolacci et al. 2010), Lee et al. (2018) show that there is no significant difference in the main results between the experiments conducted on MTurk and in the traditional laboratory, they also suggest that MTurk appears to be an important and relevant tool for researchers.

One of the main benefits of using SoPHIE via MTurk is that we can access a bigger sample size from a wide range of industries and work backgrounds than the traditional laboratory experiments where most participants are either undergraduate or graduate students. Also, from an operation efficiency point of view, conducting experiments via MTurk is much faster and more flexible than the traditional laboratory. Among the U.S. IP addresses of MTurk "workers," approximately 65% are female and 60% are over the age of 30, which is slightly younger than the U.S. Internet population (Paolacci et al. 2010). The modal household income for these "workers" ranges from $40,000 to $60,000 (Ipeirotis 2010), which is similar compared to the U.S. workforce, and 78% of them have at least a bachelor's degree, which is much higher than the average U.S. population (Ross et al. 2010).

However, there are some limitations by conducting real-time interaction experiments online, such as unexpected dropouts, network connection problems, and participants who leave the webpage unattended. Since we could neither control the nature of the Internet nor force the participants to finish the experiment, when such an event occurs, the affected group members freeze at the waiting screen. We then manually move those affected participants to the finished stage and pay them show up fees.

Money was the only incentive to all the participants, and they were paid according to their performance plus a small amount of show up fee at the end of the experiment. The better performance, the higher profit the participant could get. Average payments were \$0.6, which is in-line with an MTurk experiment average earning rate. Although the average payments were relative low compare to the traditional laboratory experiments, according to Buhrmester et al. (2011) and Paolacci et al. (2010), a lower rate of pay has been shown to make it slower for requesters to recruit participants on MTurk, but the payment level does not affect data quality.

Overall, we have a total of 1,176 U.S. MTurk "workers" who volunteered to participate and received monetary compensation according to their performance. To ensure the participants understood our experimental procedures while complying with our IRB protocol, we restricted their internet portal geographic location to the United States and only accepted skilled workers (completed at least 100 MTurk tasks with at least 95% approval rates.). Many prior MTurk research use this sample restrictions to ensure the quality of the data (Hauser and Schwarz 2016, Lee et al. 2018, Peer et al. 2014).

2.5 Experimental Results

Table 3 presents game theory predictions and summary statistics of experimental results.

Table 3. Theoretical Analysis vs. Experimental Results

	Prediction	Experimental Result				Prediction	Experimental Result		
	Equilibrium	Median	Mean	SD		Equilibrium	Median	Mean	SD
(a) $H_L C_L$					(b) $H_H C_L$				
Period 1					Period 1				
w_1	73	65	66.20	26.00	w_1	72	65	66.34	25.42
z_{s1}	109	60	66.30	38.99	z_{s1}	108	70	68.81	32.98
r_{o1}	46	50	60.23	32.59	r_{o1}	24	50	52.74	31.95
z_{r1}	23	37.5	39.89	27.46	z_{r1}	24	40	42.15	28.14
I	23	15	20.34	20.40	I	0	10	10.59	12.08
Period 2					Period 2				
w_2	62	60	60.01	23.74	w_2	72	60	67.17	29.85
z_{s2}	101	60	65.77	36.41	z_{s2}	108	60	68.21	36.61
r_{o2}	15	40	47.06	38.23	r_{o2}	24	35	38.05	27.08
z_{r2}	38	60	67.40	40.81	z_{r2}	24	45	48.65	30.01
Π_s	15,261	13,485	13,082	3,103	Π_s	15,120	13,650	13,083	3,458
Π_r	690	2,101	2,234	3,093	Π_r	589	1,615	2,068	3,338
Π_{sc}	15,951	15,861	15,316	2,639	Π_{sc}	15,709	15,620	15,151	2,247
(c) $H_L C_H$					(d) $H_H C_H$				
Period 1					Period 1				
w_1	70	69	67.27	22.55	w_1	69	65	67.70	23.25
z_{s1}	54	60	59.93	28.01	z_{s1}	53	57	59.54	30.41
r_{o1}	109	60	66.10	35.15	r_{o1}	78	58	59.80	30.65
z_{r1}	53	35	38.68	29.37	z_{r1}	55	40	43.72	27.83
I	56	15	27.42	29.98	I	23	11	16.08	12.43
Period 2					Period 2				
w_2	43	60	61.63	23.43	w_2	57	62	65.42	24.72
z_{s2}	35	50	52.80	26.31	z_{s2}	45	50	55.68	30.44
r_{o2}	34	40	41.24	31.07	r_{o2}	47	40	42.81	29.53
z_{r2}	90	60	68.66	39.01	z_{r2}	70	55	58.90	31.20
Π_s	11,152	8,650	8,785	2,655	Π_s	10,465	8,500	8,520	2,788
Π_r	3,820	2,420	2,343	2,987	Π_r	3,213	2,313	2,323	3,059
Π_{sc}	14,971	11,230	11,129	3,008	Π_{sc}	13,678	11,238	10,843	3,855

Note: $H_i C_i$ with $i - L$ or H represents a low or a high inventory holding (direct selling) cost.

Result 1: Retailers mostly under-use strategic inventory.

Table 4 provides summary statistics on strategic inventory decisions. The observed values of the strategic inventories are significantly greater than zero (one-sample Wilcoxon test with p-value < 0.01) in all four treatments, but significantly lower than predictions in three out of four treatments.

This is strong evidence that the retailer underused strategic inventory in three out of four treatments and overused in $H_H C_L$ treatment. Note that in $H_H C_L$ treatment, the equilibrium prediction for the strategic inventory level is zero, and inventory levels cannot be negative. Any deviation from the Nash equilibrium is going to result in overuse of strategic inventory.

One possible explanation of under-using inventory is that wholesale price in the first period is different than that the equilibrium predicts. Further analysis shows that this is not the explanation. We calculate the best response inventory levels based on the observed wholesale prices in the first period and find that the observed inventory levels are also lower in three out of four treatments, except the aforementioned H_HC_L treatment (one-sample Wilcoxon test, p-value < 0.01). Hence, **Hypothesis 1a is supported and Hypothesis 1b is not supported**.

Table 2.4. Strategic Inventory Results

Treatment	Equilibrium	Best-Response	Median	Mean	SD	Misalignment
(a) H_LC_L	23	35.56	15	20.34***	20.40	39.10
(b) H_HC_L	0	0.11	10	10.59***	12.08	35.22
(c) H_LC_H	56	61.72	15	27.42***	29.98	48.04
(d) H_HC_H	23	25.73	11	16.08***	12.43	34.20

***, **, * for the significance of <0.01, <0.05, 0.1.

Result 2: Retailers under-respond to holding cost and market power.

From regression analysis, we found that holding cost and market power coefficients are smaller than theory predictions, this is an evidence that the retailers under-respond to holding cost and market power.

We use the two-sample Mann-Whitney test to determine whether the retailer's inventory carry strategies are affected by changing in holding cost (h) or market power (c). If we compare strategic inventory level between (H_HC_L and H_HC_H) or (H_LC_L and H_LC_H) treatments, we found that strategic inventory level is significantly different between (H_HC_L and H_HC_H) (p-value < 0.01), but is not significantly different between (H_LC_L) and H_LC_H). Hence, **Hypothesis 2 is partially supported**.

Conversely, If we compare strategic inventory level between (H_HC_L and H_LC_L) or (H_HC_H and H_LC_H) treatments, we found that strategic inventory level are significantly different across treatments (p-value < 0.02). Hence, **Hypothesis 3 is supported**.

We now turn our attention to how much did the retailer's inventory deviate from its best-response. Table 5 presents the retailer's strategic inventory decisions under different treatments based on its best-response. First, the intercepts in all four treatments significantly lower than the best-response prediction (two-sample Mann-Whitney test, p-value < 0.01). This also suggests a consistency significantly under responding bias to inventory across all treatments. In addition, strategic inventory best-response function shows no difference in coefficients between the wholesale price and the inventory holding cost (-1.85 in both coefficients), since they are the same dollar to dollar economic value to the retailer. The actual results from pooled data show that both wholesale price and inventory holding cost are significantly lower than the predictions (one-sample Wilcoxon test, p-value < 0.01). Moreover, the retailer underweights the wholesale price more than the inventory holding cost (ratio test, p-value < 0.01). One possible explanation for that is due to our experimental design, the retailer pays the inventory purchase cost at the end of period 2, so in period 1, when the retailer decides his strategic inventory level, they put less attention on their inventory cost. To see whether the retailer responds differently on inventory holding cost and market power, we compare the inventory holding cost (-0.55) and the market power (0.16) coefficients with their best response ($inventory = \frac{25d-50h-50w_1+19c}{54\alpha}$) coefficients ($\frac{-50h}{27}$ and $\frac{19c}{27}$). Compared observed coefficients ratio with best response in inventory holding cost and market power, we find that the retailers weigh less in market power than in holding cost (ratio test, p-value < 0.01).

Thus, it appears that the retailer's strategic inventory decisions are statistically significantly influenced by the wholesale prices, inventory holding costs and market power, but with downward biases. This is third evidence that the retailer under-responds to the wholesale price, the inventory holding cost, and the market power.

Table 2.5. Regression Results on Strategic Inventory

Treatment	Intercept	w_1	h	c
Best-Response	138.89	-1.85	-1.85	0.70
C_L	26.89***	-0.09**	-0.51***	(omitted)
CH	37.94***	-0.15***	-0.59***	(omitted)
H_L	26.62***	-0.18***	(omitted)	0.18**
H_H	10.09***	-0.06**	(omitted)	0.14***
Pooled	24.15***	-0.12***	-0.55***	0.16***

***, **, * for the significance of <0.01, <0.05, <0.1

Result 3: Wholesale price in period 2 responds to strategic inventory.

Table 6. Wholesale prices Result

Treatment	Period 1 Equilibrium	Period 1 Mean	Period 2 Equilibrium	Period 2 Best-Response	Period 2 Mean
(a) $H_L C_L$	73	66.20***	62	62.85	60.01
(b) $H_H C_L$	72	66.34***	72	67.23	67.17***
(c) $H_L C_H$	70	67.27**	43	55.66	61.63***
(d) $H_H C_H$	69	67.70*	57	60.76	65.42***

***, **, * for the significance of <0.01, <0.05, <0.1

We now analyze the supplier's wholesale price in period 2. First, and somewhat surprisingly, Table 6 shows that the suppliers were mixed with over and under responding for period 2 wholesale price decisions. In particular, average period 2 wholesale prices are partially significantly lower under C_L treatment. However, average period 2 wholesale prices are significantly higher under C_H treatment (one-sample Wilcoxon test, p-value < 0.01). Also, the supplies' wholesale price decisions are not significantly different from the best-response decisions, except in $H_L C_H$ treatment. This inconsistent result suggests there may be other variables also affecting the suppliers when they were making period 2 wholesale price decisions.

Table 7 provides period 2 wholesale price linear regression with predicted variables by the best-response and also prior results from period 1, such as the market price, the profit difference between the supplier and the retailer. As one can see, the suppliers' period 2 wholesale price decisions were not only negatively related to the retailer's strategic inventories, but also positively related to prior period market price and the profit difference between the supplier and the retailer. This indicates that if the prior market price is high, the suppliers are more likely to set a high wholesale price in period 2, and the suppliers were affected by anchoring bias. One interesting finding here is that the supplier is also focused on how much profit she earned compared with the retailer. The more she earns compared with the retailer in period 1, the higher wholesale prices she is going set in period 2. We speculate when the subjects making their decisions, they have fairness concerns.

Table 7. Regression Results on Period 2 Wholesale Price

Treatment	Intercept	Inventory	Market Price 1	Profit Difference	c	R^2
(a) H_LC_L	20.45*	-0.24**	0.24**	0.003***	-	0.1326
(b) H_HC_L	20.23	-0.66***	0.30**	0.004***	-	0.2393
(c) H_LC_H	22.49**	-0.39***	0.29***	0.004***	-	0.2479
(d) H_HC_H	34.35***	-0.67***	0.22**	0.005***	-	0.2075
Pooled	12.45*	-0.41***	0.26***	0.004***	0.22**	0.2047

***, **, * for the significance of <0.01, <0.05, <0.1

Notice that the supplier underpriced in w_2 again in C_L treatment and overpriced in C_H. We suspect that the suppliers underweight use of their direct channel, in other word, it is their market power. This underweight bias on market power can also be pointed out by pooled data, we observe complete opposed signs for market cost c with a significant p-value.

We then summarize the results of our tests of Hypothesis 4. We use the Mann-Whitney two samples test (Siegel 1956) to make the comparisons given the condition on retailer carry inventory. The results show ($p < 0.03$, two-tailed) that in all treatments, the wholesale prices in period 2 are statistically significantly lower than the wholesale prices in period 1. The result shows the retailer uses strategic inventory strategy in a dual channel setting, and the supplier reacted on the retailer's inventory strategy by lowering the wholesale price in period 2. This result consistent with prior strategic inventory literature about when the supplier react on the retailer's strategic inventory strategy, she reduce their period 2 wholesale price in order to induce the retailer to order more products from the supplier (Anand et al. 2008, Hartwig et al. 2015, Guan et al. 2019, Roy et al. 2019). Hence, **Hypothesis 4 is supported**.

Next, we investigate how the inventory holding cost and the market power affect the supplier's and the retailer's selling decisions. Table 8 presents the theoretical predictions with the experimental results. We used a one-sample Wilcoxon test (Siegel 1956) to make the comparisons, and the results show that both the supplier's and the retailer's selling decisions significantly (p-value < 0.1) deviated from the predictions.

Table 2.8. Theoretical Analysis vs. Experimental Results (Selling Quantities)

	Prediction	Experimental Result				Prediction	Experimental Result		
	Equilibrium	Median	Mean	SD		Equilibrium	Median	Mean	SD
(a) H_LC_L					(b) H_HC_L				
Period 1					Period 1				
$zs1$	109	60***	66.30	38.99	$zs1$	108	70***	68.81	32.98
$zr1$	23	37.5***	39.89	27.46	$zr1$	24	40***	42.15	28.14
Period 2					Period 2				
$zs2$	101	60***	65.77	36.41	$zs2$	108	60***	68.21	36.61
$zr2$	38	60***	67.40	40.81	$zr2$	24	45***	48.65	30.01
(c) H_LC_H					(d) H_HC_L				
Period 1					Period 1				
$zs1$	54	60**	59.93	28.01	$zs1$	53	57*	59.54	30.41
$zr1$	53	35***	38.68	29.37	$zr1$	55	40***	43.72	27.83
Period 2					Period 2				
$zs2$	35	50***	52.80	26.31	$zs2$	45	50***	55.68	30.44
$zr2$	90	60***	68.66	39.01	$zr2$	70	55***	58.90	31.20

***, **, * for the significance of <0.01, <0.05, <0.1

Result 4: Both supplier and retailer selling quantities under response to wholesale price. Similar to result 2, we compare the supplier's and the retailer's selling quantity coefficients with best responses. We find that both the suppliers and the retailers were significantly under responding to the wholesale price when they are setting their selling quantity in period 1 (please see regression coefficients in Appendix D).

Theory predicts that the suppliers should sell more via direct selling channel under H_L treatment than under H_H treatment in period 1. Results show that the suppliers did not respond to different holding cost conditions when making selling decisions. One possible explanation for that is because the suppliers were focused on their wholesale prices and selling decisions and paid less attention to their competitors' embedded structure cost.

Conversely, theory predicts that the retailers sell less under H_L treatment than under H_H treatment in period 1. Results show that the retailers did not respond on different market power when making selling decision in period 1 (p > 0.2, one-tailed), and but correctly responded to market power in period 2 (p < 0.1, one-tailed). This could also be explained by the fact that when the retailers making selling decisions in period 1, they were more likely to focus on their own holding cost, and pay less to attend to the market power, where the market cost is on the supplier side.

In period 2, when the supplier and the retailer make their selling decisions, they were significantly anchoring on their prior period decisions instead responding to market power and inventory level. The potential explanation for this observation is that when the suppliers and the retailers try to maximize their own profits, they significantly underweight the response on the market power, and overlook their own cost.

Result 5: Under-respond bias always hurt the supplier and total supply chain but not the retailer.

In table 9, we observe that under C_L treatment, the retailers performed significantly better than the predictions. Conversely, under C_H treatment, the retailers performed significantly worse than the predictions. Possible reason to explain this phenomenon is because the suppliers were selling significantly lower quantities than the predictions, and the retailer took advantage of that.

Conversely, the suppliers' profit significantly lower than theory predictions regardless treatments. Due to the under-responding of strategic inventories and selling bias, the total supply chain efficiency was also significantly lower than theory predictions.

Table 2.9. Theoretical Analysis vs. Experimental Results (Profits)

	Prediction	Experimental Result				Prediction	Experimental Result		
	Equilibrium	Median	Mean	SD		Equilibrium	Median	Mean	SD
(a) H_LC_L					(b) H_HC_L				
Π_s	15,261	13,485	13,082	3,103	Π_s	15,120	13,650	13,083	3,458
Π_r	690	2,101	2,234	3,093	Π_r	589	1,615	2,068	3,338
ΠSC	15,951	15,861	15,316	2,639	ΠSC	15,709	15,620	15,151	2,247
(c) H_LC_H					(d) H_HC_L				
Π_s	11,152	8,650	8,785	2,655	Π_s	10,465	8,500	8,520	2,788
Π_r	3,820	2,420	2,343	2,987	Π_r	3,213	2,313	2,323	3,059
ΠSC	14,971	11,230	11,129	3,008	ΠSC	13,678	11,238	10,843	3,855

***, **, * for the significance of <0.01, <0.05, <0.1

Additional observations:

In our experiments, strategic inventories were used by the retailers in all treatments, even the one they should not (H_HC_L treatment). This is partially consistent with Hartwig et al. 2015, who report that strategic inventories were only used when theory predicted so, which is under low inventory holding cost. One key difference in experimental design is that they restricted subjects' decisions only on wholesale prices and inventory, other decisions were made by computer. In our treatments, we not only allow the subjects freely to make wholesale prices, ordering, selling and inventory decisions, but also add dual channel competition in each period.

In addition, we find several patterns that may be interesting.

Observation 1: The relative level of inventory is consistent with direction that predicted by theory.

Game theory predicts that the retailers should carry the highest inventory level in H_LC_H treatment, and zero inventory in H_HC_L treatment. The actual results indeed showed that subjects carried on average 27.42 inventories in H_LC_H treatment, which is the highest inventory level amount other treatments. Similarly, subjects carried on average 10.59 inventories in H_HC_L treatment, which is the lowest inventory level compared with other treatments. The overall inventory level pattern was followed as Nash equilibrium predictions with significantly under carrying bias. This means that subjects followed the equilibrium strategy to carry strategic inventories in different treatments, but they were unable to find the best solution while they were playing the game.

Observation 2: Same predicted level of inventory treatments resulted in different inventory level.

Game theory predicts that for both $\mathrm{H_LC_L}$ and H_HC_H treatments, the retailer should carry the same level of strategic inventories. Before the experiments, we carefully calibrated those two treatments to have the same level of inventory for one reason, if the result is different, we can easily point out the retailer's different reaction when he is facing different market power and cost issues.

As can be seen, in H_LC_L treatment, the retailers on average carry 20.34 inventories while in H_HC_H treatment, they only carry on average 16.08 inventories. When the retailers are facing different power and cost issues, they react statistically significantly differently (sign test, $p = 0.04$, one tailed) on strategic inventory decisions. However, if comparing absolute mean misalignment under H_LC_L and H_HC_H treatments, the retailer under both treatments made no different error (two-sample Mann-Whitney test, p-value = 0.38). One potential explanation is that individuals do not respond to holding cost nor market power as theory suggested.

Observation 3: Retailers error most on inventory level when having highest market power.

Aside from theoretical comparison, we also compare the absolute difference between the actual inventory and the best-response inventory to investigate the retailer's inventory carry strategy. Recall from Table 4 inventory misalignment (defined as the absolute difference between the actual inventory and the best-response inventory given the supplier's wholesale price, i.e. $|i - i_{BR}|$).

In H_LC_H treatment, the retailer made the largest absolute error (two-sample Mann-Whitney, p-value < 0.01). This shows that when the retailer has the most market advantages, i.e., low inventory holding cost and high market power, he tends to err the most. Conversely, when comparing inventory's standard deviation across treatments, in H_LC_H treatment, the retailer has the widest range of standard deviation. Recall from Table 4, the theoretical prediction on inventory range across four treatments is 56, which is significantly larger than the actual inventory range (16.83). This is another evidence shows that when the retailer is facing holding cost and market power issues, his strategic inventory decisions deviate from predictions.

To further investigate how different inventory levels affect the retailer's and the supplier's profit split, in Table 10 we provide the percentage of profit sharing for both periods. Note that, in period 1, the retailers gain a significantly higher percentage of total supply chain profits than game theory predictions in all treatments. This indicates that strategic inventory not only reduces double marginalization problem, it might also have a behavioral impact on the retailers seeking more equitable payoff distribution in the dual channel supply chain.

Table 2.10. Profit Sharing Percentage

	Period 1		Period 2		Total	
	Prediction	Actual	Prediction	Actual	Prediction	Actual
(a) H_LC_L Π_s	0.97	0.87	0.94	0.83	0.96	0.85
Π_r	0.03	0.13	0.06	0.17	0.04	0.15
(b) H_HC_L Π_s	0.96	0.90	0.96	0.83	0.96	0.86
Π_r	0.04	0.10	0.04	0.17	0.04	0.14
(c) H_LC_H Π_s	0.79	0.86	0.71	0.69	0.74	0.79
Π_r	0.21	0.14	0.29	0.31	0.26	0.21
(d) H_HC_H Π_s	0.83	0.86	0.71	0.70	0.77	0.79
Π_r	0.17	0.14	0.29	0.30	0.23	0.21

2.6 Behavioral Model and Estimation

We motivate the behavioral model by two main findings from the experiments: (1) individuals use less inventory than predicted by game theory[1] and (2) they under-respond to inventory when choosing wholesale prices. We observe a significant amount of decision noise in the experiments, consistent with bounded rationality.

Interestingly, we discover that bounded rationality with the quantal response framework (QRE) (McKelvey and Palfrey 1995) alone is sufficient to explain the major empirical results. This is usually not the case in operations settings (Kremer et al. 2010, Wu and Chen 2014). We speculate that since the use of inventory in this setting is strategic in nature, and there is no obvious cause for other behavioral factors. Hence, bounded rationality remains the dominant factor. Note that while bounded rationality is sufficient to explain our main findings, fairness concern is a necessary component if we want to estimate the levels of bounded rationality from experimental data[2].

Furthermore, to ensure our explanation is correct, we explore several alternatives. We test both risk aversion and loss aversion, but neither is significant[3]. We do find significant anchoring behavior on the market price of the first period when both the supplier and the retailer were making selling quantity decisions. However, since it does not contribute to the explanation to the major empirical conclusions, we leave it out of the main model[4].

2.6.1 Quantum Response Equilibrium

We find the QRE by backward induction. For ease of exposition, we adopt the following definition. Let x be decision variables, u be utility functions and γ be the bounded rationality parameter, with w_2, inv, z_{s2}, and z_{r2} to index the wholesale price, strategic inventory, the supplier's and the retailer's selling decisions in period 2.

	Decision	Bounded Rationality
wholesale price	w_2	$\gamma w2$
Inventory	inv	γinv
Supplier Selling	$zs2$	γzs
Retailer Selling	$zr2$	γzr

[1] Except in the treatment when they should not.
[2] Without the inclusion of the fairness concern, the model will be too "far" from the empirical observations that the estimated bounded rationality parameter is zero. In other words, the model will misconstrue the decision data to show no reaction to any incentives. Hence, we believe it is necessary to include this modeling feature.
[3] Both risk aversion and loss aversion are tested in the same quantal response framework. Please see Appendix E for the details.
[4] Please see Appendix E for the details.

We assume γ can be different for different decisions. Hence, let $\gamma_{w2}, \gamma_{inv}, \gamma_{zs}$, and γ_{zr} be the bounded rationality parameters for the wholesale price, strategic inventory, the supplier's and the retailer's selling decisions respectively in period 2. In addition, we assume the parameters are homogeneous across individuals, similar to past literature (Chen et al. 2012, Ho and Zhang 2008, Lim and Ho 2007, Su 2008).

2.6.1.1. Supplier and Retailer Selling Decisions in Period 2

We start with the last stage of the game where the supplier and the retailer simultaneously make their selling quantity decisions. The utilities for the supplier and the retailer, conditioned on wholesale prices in period 1 and period 2 and strategic inventory level, for the selling decisions are given by:

$$u_{s2}(x_{w1}, x_{inv}, x_{w2}, x_{zs2}, x_{zr2}) = (d - \alpha(x_{zs2} + x_{zr2}) - c)x_{zs2} + x_{w2}(x_{zr2} - x_{inv}) + x_{w1}x_{inv}$$

$$u_{r2}(x_{w1}, x_{inv}, x_{w2}, x_{zs2}, x_{zr2}) = (d - \alpha(x_{zs2} + x_{zr2}))x_{zr2} - x_{w2}(x_{zr2} - x_{inv}) - x_{w1}x_{inv}$$

where d is the market price intercept, α is the sensitivity of the market competition, and c is the supplier's per unit direct selling cost.

Since the supplier's and the retailer's selling quantity decisions are made simultaneously, a pair of distributions $(P_{zs2}(x_{zr2}), P_{zr2}(x_{zs2}))$ can satisfy the quantal response equilibrium conditions.

$$P_{zs}(zs|w_1, inv, w_2) = \frac{e^{\gamma_{zs} E_{zr}(u_{s2}(z_s, z_r))}}{\sum_{zs'} e^{\gamma_{zs} E_{zr}(u_{s2}(z_s', z_r))}}$$

$$P_{zr}(zr|w_1, inv, w_2) = \frac{e^{\gamma_{zr} E_{zs}(u_{r2}(z_r, z_s))}}{\sum_{zr'} e^{\gamma_{zr} E_{zs}(u_{r2}(z_r', z_s))}}$$

where γ_{zs} and γ_{zr} are the bounded rationality parameters for the decisions of selling quantity. Follow the same convention as in Wu and Chen 2014, when $\gamma_{zs} = 0$ or $\gamma_{zr} = 0$, the individual shows no intelligence and chooses his/her decision among all possible choices with equal probability, employing uniform random choice. When $\gamma_{zs} \rightarrow \infty$ or $\gamma_{zr} \rightarrow \infty$, the individual picks the best-response, which has the highest utility.

The expected utility of the supplier, over the retailer's quantal response distribution, is given by:

$$E_{zr}(u_{s2}(zs|w_1, inv, w_2)) = \sum zr\ p_{zr}(zr)u_{s2}(z_s, z_r)$$

The expected utility of the retailer, over the supplier's quantal response distribution, is given by:

$$E_{zs}(u_{r2}(zr|w_1, inv, w_2)) = \sum zs\ p_{zs}(zs)u_{r2}(z_r, z_s)$$

2.6.1.2 Wholesale Price Decision in Period 2

Going back one stage, we analyze the supplier's wholesale price decision for period 2. Given the supplier's and the retailer's selling quantity decision distributions, the supplier decides her period 2 wholesale price, conditioned on the retailer's strategic inventory level, the quantal response probability of choosing wholesale price x_{w2} is given by:

$$P_{w2}(w_2|w_1, inv) = \frac{e^{\gamma_{w2}E(u_{s2}(w_2,z_s,z_r))}}{\sum_{zs'} e^{\gamma_{w2}E(u_{s2}(w_2',z_s,z_r))}}$$

where γ_{w2} is the bounded rationality parameter for the decisions of period 2 wholesale price, and E represents the supplier's expected profit based on w_2,z_s,and z_r.

2.6.1.3 Strategic Inventory Decision in Period 1

Similarly, we formulate the utility of the strategic inventory decision, based on the quantal response probabilities of the subsequent decisions. In our setting, recall that the strategic inventory decision is a result of the retailer's simultaneous decisions about order and selling at period 1. When the retailer makes period 1 decisions, he also takes expected period 2 profit as his consideration. The expected utility of the strategic inventory is given by:

$$u_r(x_{w1}, x_{zs1}, x_{o1}, x_{zs1}) = (d - \alpha(x_{zs1} + x_{zr1}))x_{zr1} - x_{w1}(x_{o1}) + u_{r2}$$

The retailer's period 1 decision probability is given by:

$$P_{r1}(o_1, zr_1|w_1, zs_1) = \frac{e^{\gamma_{r1}E(u_{r1}(o_1,zr_1)+u_{r2})}}{\sum_{r1'} e^{\gamma_{r1}E(u_{r1}(o_1,zr_1)'+u_{r2})}}$$

2.6.1.4 Fairness

We incorporate fairness concerns to the utility functions for the retailer using the standard inequality aversion formulation (Cui et al. 2007, Li et al. 2019), following assumption that the retailer suffers from a utility loss if his expected profit is lower than the supplier's expected profit. We incorporate this inequality aversion into the utility as follows:[5]

$u_r = u_r - \alpha(u_s - u_r)^+$

where α is the parameter to be estimated from data, interpreted as the degree of which the retailer cares about the inequality in his profit, and this inequality aversion term only applies if the supplier's expected profit is more than the retailer's expected profit. For example, if *alpha*

[5] Note that there are more complicated formulation of fairness (e.g. Cui et al. 2007). However, as fairness is not the main focus of this paper and this particular simple formulation is sufficient to fit the data.

= 1, the retailer cares about inequity aversion as much as about his own profit. Conversely, if *alpha* = 0, the retailer does not care whether or not his profit is ”fair” compared with the supplier.

2.6.2 Behavioral Model Implications

The behavior model is designed to explain the main empirical conclusion: the retailer under use of strategic inventory, and the supplier under responding to level of inventory when setting the wholesale price in period 2. In this section, we demonstrate how bounded rationality impacts those two decisions. Based on the model, we calculate the expected decisions, with setting parameters (inventory holding cost h and supplier direct selling cost c) from the four treatments, as a function of the bounded rationality parameter γ, in the range from zero (no intelligent) to 0.04 (high intelligent) for all three decisions in period 2. We intentionally keep the bounded rationality parameter γ the same for all decisions for clear exposition. If we keep the bounded rationality parameters for some decisions constant and vary only one, we obtain similar results. In addition, we set the fairness parameter α to be zero as to isolate the impact of bounded rationality.

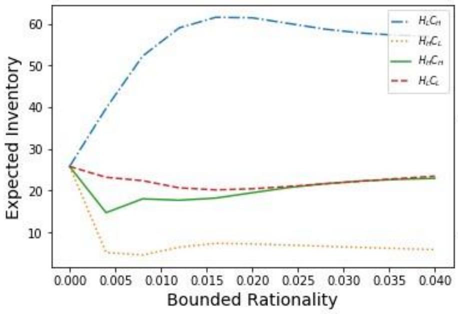
We plot the expected inventory and the expected wholesale price as a function of the given bounded rationality, all else equal.

Model Implication 1: Underuse of Strategic Inventory

One of the main conclusions is that the retailer significantly underuses strategic inventory in three out of four treatments. Please see Figure 2 for an illustration of how the level of strategic inventory, expected over the quantal response probabilities, changes as the level of bounded rationality changes. With the setting parameters from the original treatments, we plot the expected inventory level over the quantal response equilibrium distribution as a function of the level of bounded rationality.

Recall that strategic inventory decisions are a result of the retailer’s simultaneous decisions about order and selling at period 1. If the retailer has no intelligence (i.e. $\gamma_{r1} = 0$) about how much strategic inventory to carry, he makes uniform distributed inventory decisions in period 1, without responding to incentives. Hence, the model predicts the same expected inventory levels for all 4 treatments in this scenario.

Under the same predicted level of inventory treatments (H_LC_L and H_HC_H), if the retailer is rational, he will carries the same level of inventories (23 in this calibration) in both treatments. If he is less rational, he carries more inventory under H_LC_L than H_HC_H treatment due to holding cost and market power vary across two treatments. This is consistent with experimental observations, and further supports the insight of retailers under use of strategic inventory because of bounded rational, and the retailer responds differently when holding cost and market power changes.



	Inventory under Nash Eq	γ = 0.004 Expected Inventory	Observed Inventory
H_LC_H	56	39.77	27.42
H_HC_L	0	5.21	10.59
H_HC_H	23	14.75	16.08
H_LC_L	23	24.07	20.34

Figure 2.2. Expected Inventory Response to the Bounded Rationality[6]

Model Implication 2: Wholesale Price "under"-responds to Strategic Inventory

Similarly, please see Figure 3 for an illustration of how the wholesale price in period 2, expected over different levels of inventory, changes as the level of bounded rationality changes.

The model predicts that when the level of strategic inventory increases, the wholesale price in period 2 decreases. As the bounded rationalities in period 2 decisions ($\gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}$) increase, the expected wholesale price in period 2 is closer to the prediction. Here we use different level of bounded rationalities to represent the decisions ($\gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}$) in period 2 as treatment parameters to demonstrate how the expected wholesale price responds to the different levels of strategic inventory. When the bounded rationalities increase from 0 to 0.03, the slope of expected wholesale price in period 2 becomes steeper and closer to the prediction[7].

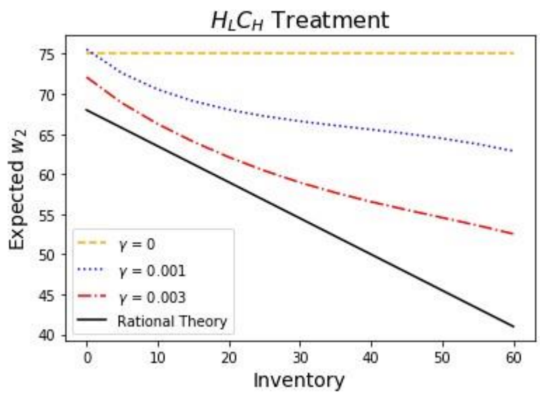


Figure 2.3. Wholesale Price Response to Inventory with Different Bounded Rationalities

[6] The model works without estimation.

[7] We only use H_LC_H treatment, the result is consistent across all treatments.

Profit split in period 2

We also explore the impact of under-responding on strategic inventory behavior on the profit performance of the supplier and the retailer in period 2. We use high and low bounded rationalities for wholesale price, supplier's and the retailer's selling quantities ($\gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}$) to mimic the decision process of each participant in period 2. From the resulting decisions probability distributions, which correspond to profits given their choices of a particular decision, we calculate the expected supplier's and the retailer's profit for period 2.

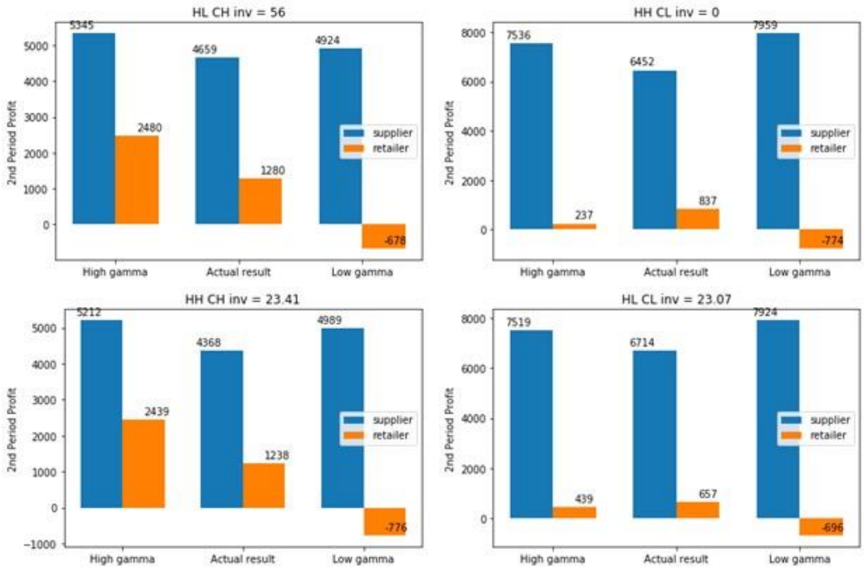


Figure 2.4. Expected Profit in Period 2 to the Bounded Rationality

Figure 4 shows the supplier's and the retailer's profits if they were fully rational, actual profit, and completely random. As illustrated above, the retailer's profit will increase if both the supplier and the retailer are fully rational under C_H treatment. Interestingly, the retailer's profit will decrease if they are fully rational under C_L treatment. One explanation for that is because under C_L treatment, the less rational supplier gives the retailer more opportunity to earn higher profit, because she is not optimizing her direct channel sales. The supplier's profit will increase if they are fully rational to the supply chain and applying "theoretically" optimal decisions under all treatments.

Next, we add the actual profit they earn from period 1 and compare it with predicted total profit (Figure 5).

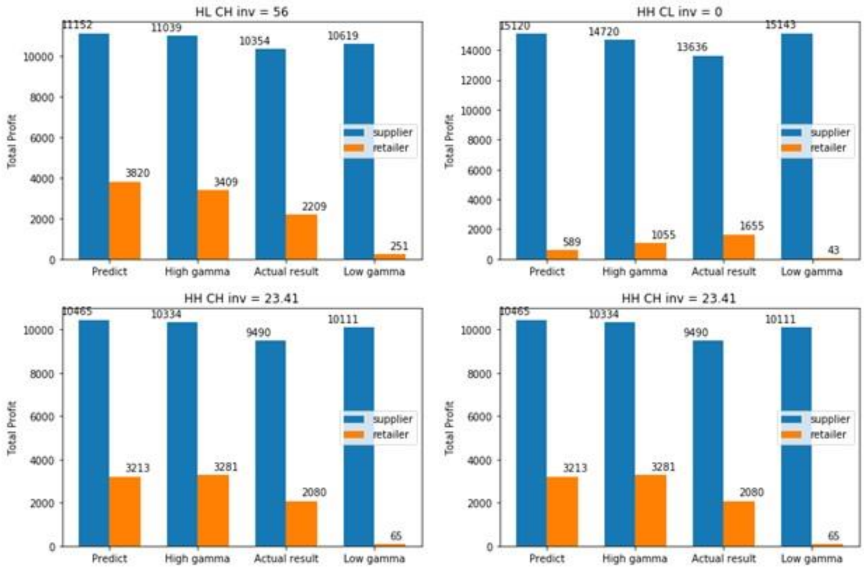


Figure 2.5. Expected Total Profit to the Bounded Rationality

The comparison is built on actual profit the supplier and the retailer earned plus expected profit given different gamma value. If we compare actual results with predictions, we notice that both the supplier and the retailer were under performed. Assuming both the supplier and the retailer have high gamma value, which means assuming they are fully rational in period 2, we see that the supplier's profit is very close to its prediction, and the retailer's profit is not only close to its prediction, but even higher than the prediction in 3 out of 4 treatments.

2.6.3 Model Estimations and Results

We use the maximum likelihood method to estimate the parameters of the model for period 2, given in section 6.1. There are 5 behavioral parameters, ($\gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}, \alpha$), representing bounded rationality for the three decisions (wholesale price, supplier's selling quantity, and retailer's selling quantity), and fairness concerns. Similar to Chen et al. (2012), we assume the behavioral parameters are homogeneous across individuals. Since the decisions are assumed to be conditionally independent, the loglikelihood function is simply the sum of the log of the probabilities of each decision. The loglikelihood function for period 2 is, hence, given by:

$LL(\theta) = log(P_{w2}(x_{w2})) + log(P_{zs}(x_{zs})) + log(P_{zr}(x_{zr}))$

where $\theta = \gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}, \alpha$ are the behavioral parameters, and the decisions (x_{w2}, x_{zs2}, x_{zr2}).

Table 11 summarizes the estimation results based on the standard maximum likelihood method.

Table 11. Model Estimation Results

	H_LC_L	H_HC_L	H_LC_H	H_HC_H
-Log likelihood	984.04	977.94	923.71	872.34
γ_{w2}: wholesale price bounded rationality	0.001101 (0.000)	0.000207 (0.000)	0.001833 (0.000)	0.002515 (0.000)
γ_{zs2}: supplier selling bounded rationality	0.000860 (0.000)	0.000092 (0.005)	0.001158 (0.000)	0.001006 (0.000)
γ_{zr}: retailer selling bounded rationality	0.000387 (0.003)	0.000524 (0.000)	0.000615 (0.000)	0.000923 (0.000)
α: fairness	0.655697 (0.003)	0.465824 (0.009)	0.541478 (0.000)	0.393491 (0.002)

Note: p-values are in parentheses

Estimation Result 1: Individuals are bounded rational.

One of the main empirical conclusions of the paper is that the supplier is under-responding to the level of strategic inventory, and the retailer is under-responding to the market power. Bounded rationality can explain these results.

Please see Table 11, we use the likelihood ratio test to check whether the parameter is significantly different from zero (no intelligence). The results show that the bounded rationality parameter for all the decisions ($\gamma_{w2}, \gamma_{zs2}, \gamma_{zr2}$) are significantly different from 0 with p-value less than 0.01.

In all treatments, both suppliers and retailers exhibit some rationality, as their bounded rational parameters to be greater than 0. At the same time, their decisions are significantly deviating from the Nash equilibrium. Thus, we conclude that both suppliers and retailers are boundedly rational. Bounded rationality is also consistent with wholesale prices under-responding to the levels of strategic inventory.

Estimation Result 2: The bounded rational parameters are not the same in the H_HC_H and H_LC_L treatments

Theory predicts that the retailer should carry the same level of strategic inventory in the H_HC_H and H_LC_L treatments. Observation results show that on average the retailer carries more strategic inventory in the H_LC_L treatment than the H_HC_H treatment. In order to test whether the bounded rationalities in their decision responses are different, we adopted a moderating test approach where pooled paired two treatments, and compare a restricted model assuming all parameters are the same for each decision under both treatments, with a full model assuming one of the decision parameters can vary with the treatment.

Here is the formulation for testing γ_{w2} illustrating the method.

$LLK = -2(LL(\theta full(xw2, xzs, xzr)) - LL(\theta restricted(xpooled(w2), xpooled(zs), xpooled(zr)))$

We use the likelihood ratio test to determine if bounded rational parameters are the same across treatments. Specifically, we test each individual parameter, restricting it to the same across the two treatments, against the alternative that the parameter can vary independently.

Please see Table 12 for the results. The p-values of the likelihood ratio tests for the 3 parameters are all less than 0.01. This is strong evidence that the bounded rationality levels differ across between treatments. The result indicates in real world practice, decision makers' bounded rationalities are different.

Table 2.12. Log Likelihood Ratio Test

Model	-Log likelihood	p-value
Restricted Model	1928.72	
Vary in w_2	1924.78	0.005
Vary in $zs2$	1913.73	0.000
Vary in z_{r2}	1921.30	0.000

In theory, both H_LC_L and H_HC_H should result in the same level of strategic inventory, hence they have the same response in period 2 decisions.

The estimate of bounded rationalities for wholesale price, supplier selling quantity, and the retailer quantity are significantly higher in the H_HC_H treatment compared to the H_LC_L treatment, with a pairwise comparison (p-value < 0.01). In other words, H_HC_H treatment results in a much higher rationality compared with H_LC_L treatment. This suggest that higher costs (both inventory and marketing cost) are salient and individuals pay more attention (i.e. less boundedly rational) when the costs are high.

Modeling Result 3: Retailer has fairness concerns.

Fairness is highly significant for the retailer. Intuitively, when the supplier makes more profit than the retailer, he has inequality aversion. This result is consistent with prior literature that when competition exists, fairness has an effect on decisions (Cui et al. 2007, Katok et al. 2014, Li et al. 2019).

2.7 Conclusion and Discussion

This study is the first to investigate, from a behavioral perspective, of the impact of strategic inventory in a multiple period dual channel supply chain system. We employ a combination of game theory, human subject experiments, behavioral modeling, and numerical analyses. Theoretical models predict that in a two-period dual channel supply chain, if the inventory holding cost is low enough, the retailer carries strategic inventory that can reduce a supplier's monopoly power on products in order to force the supplier to decrease wholesale price in a later period. This effect is impacted by the inventory cost, and the relative market power, captured by a marketing cost on the side of the supplier.

We conduct a series of human subject experiments and find that retailers under-use strategic inventory. That is, they do not carry as much inventory as theory has predicted. In addition, they do not respond to inventory cost nor market power as much as the theory suggested. Interestingly, they respond to inventory cost ”more”, compared to the market power. Secondly, the supplier responds to strategic inventory by lowering the wholesale price in period 2, but not as strongly as predicted. In turn, the second period quantity decisions also under-respond to the wholesale price, on the parts of both the supplier and the retailer.

We pinpoint bounded rationality as the main driver of these behaviors. We constructed a behavioral model based on the popular quantal response equilibrium framework, and find the model prediction consistent with observed behaviors. This is consistent with a large volume of behavioral operations literature dated back to Su 2008 (Chen et al. 2012, Donohue et al. 2019, Moritz et al. 2013).

From a managerial perspective, this paper suggests that, because of bounded rationality, strategic inventory is not as effective as suggested by theory. In addition, the supply chain seems to be more sensitive to the changes in inventory costs, compared to a ”similar”[8] change in market power. In practice, both the supplier and the retailer should raise awareness of the less invisible market power.

The main limitation of this study is the parsimonious design that ignore a number of complications in practice. For instance, we look at a one-supplier-one-retailer setting where, often, there are multiple suppliers and retailers competing. We assume deterministic demand and common knowledge on supply and demand information, a simplification from practice. Expanding the study to cover some of these limitations are interesting paths for future research.

[8] Defined by a level of market power change that results in the same inventory level change caused by the said changes in inventory costs.

Chapter 3

Strategic Disposal or Strategic Inventory? Theory and Experiments

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3.1 Introduction

Anand et al. (2008) show that in a multi-period supply chain, the retailer may use inventory as a strategic tool to nudge the supplier to lower the wholesale price in a later period. Moreover, under certain conditions, not only the retailer, but also the supplier can benefit from this way of using inventory because it mitigates the double marginalization problem.

This *strategic inventory* has become an important operations management topic and attracted much attention in the literature (e.g., Anand et al. 2008, Desai et al. 2010, Guan et al. 2019, Roy et al. 2019, Yang et al. 2018). As far as we know, these studies assume the market demand is deterministic and is either linear in price or modeled as discrete types. In such a setting, the inventory level is modeled as a decision variable and retailers are assumed to have complete control. However, in practice, market demands are often stochastic. Since the inventory level depends on demand realization, it no longer can be controlled perfectly. This possibility suggests new considerations regarding the role of inventory as a strategic lever. The goal of this paper is to fill this gap in the literature, and determine the role of strategic inventory when demand is stochastic and inventory is uncertain. As such, we use a newsvendor formulation of the retailer as opposed to a linear-price-demand model, the common approach in the current literature.

Employing game theoretic analysis, and somewhat to our surprise, we find, under the right conditions, it is advantageous for the retailer to commit to dispose of inventory. That is, the retailer should destroy any products that it cannot sell, and let the supplier know of its commitment to such a plan in advance of wholesale price determination. This result is the complete opposite of the main result of the current strategic inventory literature with deterministic and linear demand, where inventory is used to strategically lower wholesale prices. We refer to this phenomenon as *strategic disposal*. Disposing inventory is also practiced in some business, although not without controversies. For example, Amazon was reported to have destroyed millions of unsold items in Britain and France (Hamilton 2019). British luxury fashion brand Burberry burned over $37 million worth of products in 2017 (Dalton 2018). We offer another potential explanation.

The main reason why the retailer prefers strategic disposal with stochastic demand, while choosing inventory carryover with deterministic demand, is rooted in how well the retailer can control its inventory carryover. In the deterministic demand setting, the retailer can set any inventory level needed to nudge the wholesale price. However, this is no longer true for stochastic demand setting. In this case, the retailer can only influence the inventory by its order. If the retailer orders more, it is likely but not guaranteed that it will end up with more inventory.

This uncertainty "dilutes" the ability of the retailer to influence wholesale prices via inventory. In fact, to achieve the right expected level of inventory in the second period, the retailer has to order too much, and gives the supplier an opportunity to raise wholesale prices in the first period to extract more surplus. Hence, under the right condition, it is to the retailer's advantage to commit to inventory disposal and side-step this problem. This result depends on two important parameters of the setting. The first is the production cost of the supplier which affects its ability to set wholesale price and extract surplus from the retailer. The second is the inventory holding cost of the retailer, which affects the desirability, on the part of the retailer, to use inventory. We find that inventory disposal becomes an attractive option when the production cost is low because the supplier has more power to extract surplus from the retailer, rendering inventory less useful as a strategic tool.

Furthermore, it is well known that individuals do not always follow game theoretical predictions. In this case, disposing of inventory as a strategic solution may be in conflict with people's non-pecuniary preferences such as an aversion to waste. This is particularly succinct from a sustainability perspective (Rockstrom et al. 2009). Hence, we turn to human-subject experiments, an increasingly popular research method in operations management. We find, indeed, human subjects, in the role of the retailer, favor inventory carryover opposed to committing to inventory disposal, contradicting game theory.

We find that the discrepancies between theory and observations can be explained by a combination of bounded rationality, past demand anchoring and overconfidence. We test this explanation against several alternatives, most notably waste aversion, and find that our model provides the best explanation for the data.

This paper is organized as follows. Section 2 summarizes the related theoretical and behavioral literature in the strategic inventory in the inventory management and multi-period newsvendor problem. Section 3 describes the model setting. §4 details the research questions, experimental design and protocol. The statistics results are shown in §5. Section 6 discusses the behavioral model and provides explanations. Lastly, we conclude the paper with a discussion of the research, some limitations, and future extensions of this work in §7.

3.2 Literature Review

Three streams of literature are relevant to this study: strategic inventory in the inventory management, multi-period newsvendor problem, and the newsvendor problem from the perspective of behavioral operations management.

Anand et al. (2008) show that under certain conditions, the retailer can use strategic inventory as a competitive tool in a multi-period supply chain in order to nudge the supplier to lower the wholesale price in a later period. Although the strategic inventory is carried by the retailer, it not only benefits the retailer, it may also benefit the supplier and the total supply chain, because of the reduction in the degree of double marginalization. Recent experimental studies have shown that the retailer uses strategic inventory as theory prediction in a two-period supply chain setting (Hartwig et al. 2015), but sometimes, they tend to show an under-responding bias (Lang et al. 2021). Most research in this stream of the literature assumes deterministic demand with the price to be linear in the selling quantity. In this paper, we use a newsvendor setting with stochastic demand. Worth noting is that once demand is stochastic, inventory levels also become stochastic. Hence, our definition of "inventory use" is different from this stream of literature. We define "inventory use" as whether the retailer is committing to carry inventory.

The second stream of literature relates to theoretical research in multi-period newsvendor problems. Matsuyama (2006) investigates an initial inventory level of each period that may maximize the expected profit in a multi-period newsvendor setting, which takes account of unsatisfied demand and unsold quantity. Altintas et al. (2008) propose an efficient quantity-discount scheme as opposed to traditional all-units quantity discount contract under multi-period newsvendor setting. Huang et al. (2011) study a multi-product competitive newsvendor problem with shortage penalty cost and partial product substitution. They show that competition always results in a higher total inventory level, even with the product substitution. We expand this area of research by investigating the option of disposing inventory.

Experimental studies in behavioral operations management have documented that individuals do not follow theory prediction and often suffer from behavior biases, such as overconfidence (Ren and Croson 2013). Individual decision-maker is often noisy and usually modeled as a stochastic process, interpreted as bounded rationality (Su 2008). Some other models in the literature consider reference point and anchoring (Bolton and Katok 2008, Bostian et al. 2008). We extend this literature to consider strategic disposal with human-subject experiments and a behavioral model to explain the results.

As far as we know, this paper is the first to examine the role of stochastic demand, from both the theoretical and also behavioral perspective, in strategic inventory. We are the first to propose strategic disposal, the opposite of strategic inventory, as an inventory management strategy. We are also the first to address the relevant behavioral issues in this setting, and provide an explanation of why, though theoretically sound, strategic disposal is not always preferred by human decision-makers.

3.3 Model and Game Theory Analysis

We employ a supplier-retailer game as our main setting. The retailer is modeled as a newsvendor to capture the stochastic nature of the demand, the main consideration of this paper. In the first stage of the setting, referred to as the *commitment stage* in the rest of the paper, the retailer decides whether to commit to either *inventory disposal* or *inventory carryover*. Then the supplier and retailer will engage in two periods of a standard wholesale price game where the supplier sets wholesale price w and the retailer decides on order quantity o.

Note that we assume the retailer has the power to commit in the commitment stage. Since the retailer sets his order decisions before demands are realized, the commitment rule is automatically enforced. If the retailer commits to inventory disposal, inventory not sold at the end of the first period will be disposed of, at no cost. If the retailer commits to inventory carryover, unsold inventory in the first period will be carried over to the second period.

Table 3.1. List of Notations

p	market price
c	supplier production cost
h	inventory holding cost
d_1	market demand in period 1
d_2	market demand in period 2
w_1	wholesale price in period 1
w_2	wholesale price in period 2
o_1	order quantity in period 1
o_2	order quantity in period 2
i	inventory

The following table summarizes the sequence of events for the setting.

Table 3.2. Sequence of Events

Commitment Stage	Retailer commits to disposal or inventory carryover	
	Commit to Disposal	Commit to Inventory Carryover
Period 1 stage-w	Supplier sets wholesale price	Supplier sets wholesale price
Period 1 stage-q	Retailer sets ordering quantity	Retailer sets ordering quantity
	Dispose Unsold products	inventory (i) = $max(o_1 - d_1, 0)$ Retailer pays inventory holding cost
Period 2 stage-w	Supplier sets wholesale price	After observing the inventory size, Supplier sets wholesale price
Period 2 stage-q	Retailer sets ordering quantity	Retailer sets ordering quantity

The total profits, over the whole game, of the supplier and the retailer are as follows:

$$\pi_s = (w_1 - c)o_1 + (w_2 - c)o_2$$

$$\pi_r^{Disposal} = pEmin(o_1, d_1) - w_1 o_1 + pEmin(o_2, d_2) - w_2 o_2$$

$$\pi_r^{Inventory} = pEmin(o_1, d_1) - w_1 o_1 - ih + pEmin(o_2 + i, d_2) - w_2 o_2$$

where $i = Emax(o_1 - d_1, 0)$.

We assume that the market demand (d) in each period follows a continuous uniform distribution $U[0,1]$, similarly to Becker-Peth et al. 2020. Note that, in the experiments, we use a uniform demand distribution that ranges from 0 to 100. The problem is homomorphic with respect to uniform distributions of the form $U[0, B]$ for general values of B. It is straightforward to show that the solution (i.e., order quantity) in the case of uniform demand $U[0,1]$ is the solution for the case of $U[0, B]$ if scaled by a factor of B. Please see Appendix A for more details. For the rest of the paper, for simpler exposition, we will focus on the case where the demand distribution is $U[0,1]$.

If the retailer commits to disposal, the two-period setting becomes two independent single period newsvendor problems. Thus, it is straightforward to calculate the supplier's wholesale price and the retailer's order quantity, respectively, as follows:

$$w_1^* = w_2^* = \min\left(p, \frac{p + c}{2}\right)$$

$$o_1^* = o_2^* = \max\left(\frac{p - c}{2p}, 0\right)$$

Moreover, the supplier's, the retailer's, and the supply chain's profit over two periods, of this disposal scenario, are given by:

$$\pi_s^{Disposal} = \frac{(p - c)^2}{2p}$$

$$\pi_r^{Disposal} = \frac{(p - c)^2}{4p}$$

$$\pi_{sc}^{Disposal} = \frac{3(p - c)^2}{4p}$$

If the retailer commits to inventory carryover, the two-period setting is connected by the inventory size. Please see Appendix A2 for the detailed mathematical analysis.

3.3.1 Theoretical Analysis Comparison

We characterize the pure strategy Nash equilibrium and summarize the results in Table 3. Please see Appendix A for full solutions and associating proofs.

Table 3. Game Theory Prediction

	Condition A met: Commit to Disposal	Condition 1 met: Commit to Inventory Carryover	Condition 2 met: Commit to Inventory Carryover
Wholesale Prices	$w_1 = \frac{p+c}{2}$ $w_2 = \frac{p+c}{2}$	$w_1 = \frac{1}{98p}(-10c^2 + 12ch + 16h^2 + 62cp - 12hp + 46p^2 + x)$ $w_2 = \frac{1}{36}(18c + 18p - \frac{1}{p}(c - 4h - p + \frac{1}{7}y)^2)$	$w_1 = \frac{1}{98p}(-10c^2 + 12ch + 16h^2 + 62cp - 12hp + 46p^2 - x)$ $w_2 = \frac{1}{36}(18c + 18p - \frac{1}{p}(c - 4h - p + \frac{1}{7}z)^2)$
Order Quantities	$o_1 = \frac{p-c}{2p}$ $o_2 = \frac{p-c}{2p}$	$o_1 = \frac{1}{21p}(7c - 28h - 7p + y)$ $o_2 = -\frac{1}{36p^2}(18cp - 18p^2 + (c - 4h - p + \frac{1}{7}y)^2)$	$o_1 = \frac{1}{21p}(7c - 28h - 7p + z)$ $o_2 = -\frac{1}{36p^2}(18cp - 18p^2 + (c - 4h - p + \frac{1}{7}z)^2)$
		$I = \frac{1}{882p^2}(7c - 28h - 7p + y)^2$	$I = \frac{1}{882p^2}(7c - 28h - 7p + z)^2$

where $x = \sqrt{2}\sqrt{(5c + 4h - 5p)^2(2c^2 - 8ch + 8h^2 - 11cp + 8hp + 9p^2)}$
$y = \sqrt{169c^2 - 536ch + 592h^2 - 842cp + 536hp + 673p^2 - 12x}$
$z = \sqrt{169c^2 - 536ch + 592h^2 - 842cp + 536hp + 673p^2 + 12x}$

3.3.2 Conditions for Committing to Disposal

In this section, we discuss the main theoretical result. We find that the commitment decision depends on the inventory holding cost and the production cost.

Proposition 1. If h and c satisfy Condition A in Appendix A3, the equilibrium strategy is committing to inventory disposal. Otherwise, the retailer commits to inventory carryover. Please see Appendix A3 for the mathematical details.

Proposition 1 establishes the main result with the conditions where the retailer should commit to disposal. Note that Condition A is complex and non-intuitive. We employ a numerical example (please see Figure 1) to illustrate. Figure 1 includes an illustration of the commitment choice (left figure) and also the corresponding ordering choice (right figure) as a heat map.

This model has three exogenous parameters: the market price p, the production cost c, and the inventory holding cost h. Without the loss of generality, we normalize the market price to 1 ($p = 1$), the production cost (c) and inventory holding cost (h) should be interpreted as the fraction of the market price. If the production cost is equal to or higher than the market price, the solution is trivial (i.e., $order = 0$ and no sales), we only consider the range of production cost to be between 0 and 1 (i.e., $0 \leq c \leq 1$). We also limit the inventory holding cost to be in the same range (i.e., $0 \leq h \leq 1$) as it is unlikely that inventory costs will be higher than that of the market price.

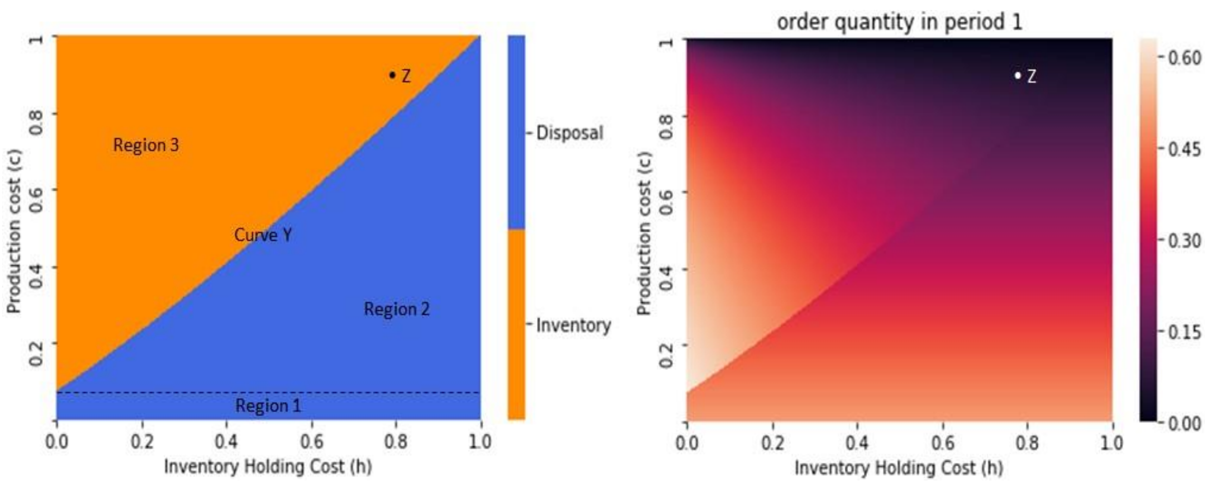

Figure 3.1. Optimal Choice of Retailer

The retailer should commit to disposal when c is lower than a particular threshold (Region 1)[9] independent of inventory holding cost. When the production cost is higher than this threshold, committing to inventory carryover (Region 3 in the Figure 1) becomes possible, as long as the inventory holding cost is low enough (to the left of threshold Curve Y). Intuitively, when the production cost is low, there is more room for the supplier to raise wholesale price in the first period, if the retailer decides to carry inventory, which leads to a higher cost and lower profits, compared to committing to disposal.

One curious observation is that sometimes, when the inventory holding cost is high and when the sum of the production cost and the inventory holding cost sum up to more than the market price of 1 (please see point Z as an example), the retailer should still commit to inventory carryover. While, in this situation, a unit to be carried over will result in a loss in profit, this loss cannot be avoided with certainty since any level of ordering will result in some chance of unsold units by the end of the first period. As such, it can still be advantageous to commit to inventory carryover to take advantage of the better overall wholesale price.

3.4 Experimental Design and Protocol

The main conclusion of the game theory analysis, illustrated by Figure 1, is that the retailer will commit to inventory disposal when the production cost is low enough (region 1). Prior literature has shown that individuals often violate standard theoretical assumptions (Donohue et al. 2019). Hence, we design and conduct human-subject experiments to test the main conclusion.

3.4.1 Experimental Design

We opt to employ a parsimonious two-treatment design for the experiments. The main empirical question is whether decision-makers commit to the "correct" strategy predicted by the theory as illustrated in Figure 1. The model setting is characterized by 4 parameters (market price p, production cost c, inventory holding cost h, and demand distribution d). We arbitrarily set p to 120 and h to 30[10]. The market demand in each period is a discrete uniform distribution ranging from [0, 100].

[9] The normalized threshold is $\frac{941-121\sqrt{57}}{384} \approx 0.0715$

[10] In practice, inventory holding cost is about 20% - 30% of its value (Jacobs and Chase 2016).

Committing to disposal is a non-intuitive strategy. From a behavioral perspective, multiple behavioral factors would make disposal unattractive. There are many negative consequences of wasting that impact the environment, economy, and society (Rockstrom et al. 2009). Research suggests that consumers have the disutility of wasting a purchase that will go unconsumed (Bolton and Alba 2012). Already purchased inventory invokes the endowment effect. Money spent on inventory may be construed as a sunk cost. In nature, there is a physiological impact in people's minds that they tend to feel bad or guilty about wasting (Evans 2012). Bounded rationality may render decision-makers less sensitive to complicated strategic consideration.

Hence, we design the first treatment with a production cost of 0, referred to as the *low production cost* treatment. With the production cost at the extreme value of 0, the incentive to commit to disposal is strongest, and committing to disposal is the equilibrium strategy independent of the level of inventory holding cost h. Hence, we provide the most favorable environment for the committing to disposal strategy to emerge.

We also use a *high production cost* treatment with a $c = 40$. In this case, we set the production cost higher enough so that committing to inventory carryover is indeed the equilibrium strategy and will serve as a contrast to the low production cost treatment.

In the experiments, participants were randomly assigned the role of supplier or retailer. A supplier and a retailer were randomly paired and interacted for one and only one round of the game, with the sequence of events summarized in Section 3 Table 2. The following table summarizes the experimental design. We assume market price, production cost, inventory holding cost, and market demands are common knowledge to the supplier and the retailer.

Table 3.4. Experimental Design

Treatment	Period 1 Demand	Period 2 Demand	Production Cost (c)	No. of Participants
Low Production Cost	[0, 100]	[0, 100]	0	402
High Production Cost	[0, 100]	[0, 100]	40	404

Notes. 1. In all treatments, market price $p = 120$, holding cost $h = 30$.
2. Market demand in each period is uniformly distributed.

3.4.2 Experiment Protocol

We followed standard economic experimental procedures and used no deception. After reading the instructions, participants are required to pass a quiz and two practice rounds (play the role of the supplier against the computerized retailer, and play the role of the retailer against the computerized supplier) to ensure that they understood the task. In all treatments, participants were randomly assigned a role and paired in groups of two to form a one supplier one retailer group to play the game. To ensure that complexity was not a driver of any results, a decision support tool was provided. Specifically, when deciding the wholesale price in each period, the suppliers had the ability to enter hypothetical wholesale price, retailer order quantity, and possible realized demand, in order to observe the potential profits for themselves and their retailers. After observing the wholesale price set by their suppliers, the retailers also had the ability to enter hypothetical order quantity and possible realized demand, in order to observe the potential profits for themselves and their suppliers.

The experimental software was programmed in SoPHIE (https://www.sophielabs.com), please refer to Appendix B for screenshots. A total of 806 participants were recruited on Amazon Mechanical Turk, referred to as MTurk in the rest of the paper (Lee et al. 2018). We only accept high quality workers (completed more than 100 MTurk tasks with at least 95% approval ratings) as our experimental subjects (Chen et al. 2021). MTurk provides a diverse set of subjects compared to the experiment conducted on university campuses. Our participants are US based Internet users, aged between 18 to 77 with a mean of 37. Approximately, 49% are female, 74% are white/Caucasian, 73% have at least an associate degree, and 49% household income is greater than $60,000.

3.5 Experimental Results

Table 5 provides game theory predictions and summary statistics of experimental results.

Table 3.5. Summary Statistics of the Experiments

	Low Production Cost		High Production Cost	
	Theory	Actual	Theory	Actual
Commit to disposal	100%	37.81%	0%	28.22%
w_1	60	71.77***	90.03	75.65***
w_2	60	67.95***	74.41	75.68*
o_1	50	54.50***	43.17	51.37***
o_2	50	45.75**	28.67	45.49***
inventory	-	16.40***	9.32	13.74
π_s	6000	6982***	3201	3363
π_r	3000	1977***	1374	1670*
π_{sc}	9000	8959	4575	5034**

Note: 1. Wilcox Test compared with Theory; 2. ***p < 0.01, **p <0.05, *p <0.1.

Result 1: Retailers choose to commit to disposal more often in the low production cost treatment, compared to the high production cost treatment, as suggested by theory.

Theory predicts that the retailers should commit to disposal in the low production cost treatment, and commit to inventory carryover in the high production cost treatment. Figure 2 reports the percentage of the retailers who committed to disposal across treatments. The frequency of committing to disposal is significantly higher in the low production cost treatment compared to the high production cost treatment, as suggested by theory (proportion test with p-value = 0.020). In addition, theory predicts that the retailer should not commit to disposal in the high production cost treatment. Actual observations are somewhat consistent with this prediction as the empirical frequency of committing to disposal is well below 50%. This suggests subjects do respond to profit motive although their decisions are noisy (i.e., frequency is in-between 0% and 100%).

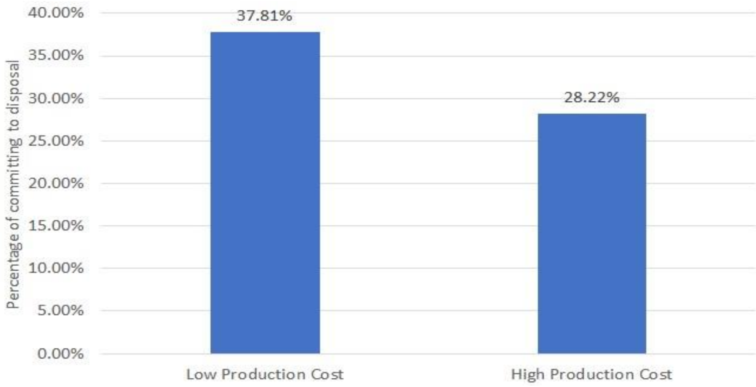

Figure 3.2. Percentage of Committing to Inventory Disposal

Result 2: Retailers under-commit to disposal.

We compare the frequencies of committing to disposal and committing to inventory carryover in each treatment using the proportion test. Result shows that the probability of committing to disposal is significantly less than the probability of committing to inventory carryover in all treatments (p-value < 0.001). Also, the probability of committing to disposal is significantly (Binomial test with p-value < 0.001) different from game theory prediction. This is strong evidence that the retailers under-committed to disposal in the low production cost treatment, where theory suggests otherwise.

A natural follow-up question is whether this behavior of under-committing to disposal is incentive driven, or caused by other behavioral factors. Figure 3 shows that the retailers made significantly higher (Wilcoxon test, p-value < 0.001) profit[11] when committing to inventory carryover compared with disposal. This suggests the retailers committing more frequently to inventory carryover is driven by profit motive. However, the subsequent decisions, namely the

[11] Actual profits are plotted in the figure. However, the conclusion will be the same if expected profits are used.

wholesale price and the quantity decisions, may exhibit biases resulting in lower than theoretically predicted profits when the retailers commit to disposal.

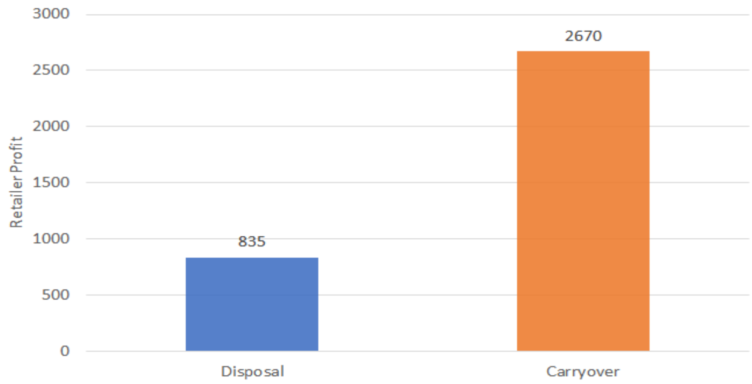

Figure 3.3. Retailer Profit

Result 3: Suppliers do not respond to commitment options when deciding the wholesale prices, inconsistent with what theory suggests.

Game theory predicts that the supplier will set a lower wholesale price in period 1 if the retailer commits to disposal compared to inventory carryover. Figure 4 shows the average wholesale price set by the suppliers observing the commitment options. Using regression analysis with a commitment option dummy, we do not find evidence (p-value > 0.241) to support that the suppliers set different wholesale prices in period 1 when responding to the commitment options.

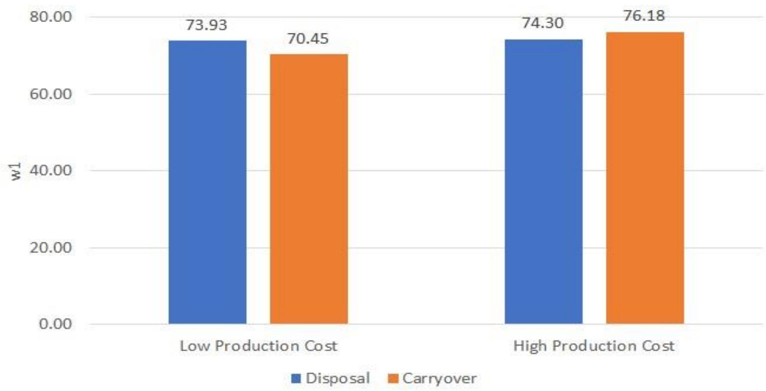

Figure 3.4. Wholesale Price in Period 1

Recall, from Section 3, if the retailers commit to inventory carryover, the suppliers will set a higher wholesale price in the first period and that outweighs the benefits of inventory carryover as well as the lower wholesale price, driven by a reduced willingness to pay caused by inventory, in the second period. Hence, the predicted weighted average wholesale price is lower if the retailer commits to disposal compared to inventory carryover. Figure 5 displays the weighted average wholesale price set by the suppliers given the inventory options. Regression analysis with inventory option dummy indicates that weighted average wholesale price is actually significantly higher (p-value = 0.034), as opposed to the predictions, when the retailer commits to the disposal option compared with the carryover option in the low production cost treatment, but not significant different in the high production cost treatment. This supports the conclusion that the suppliers did not correctly respond to the commitment options when deciding the wholesale prices.

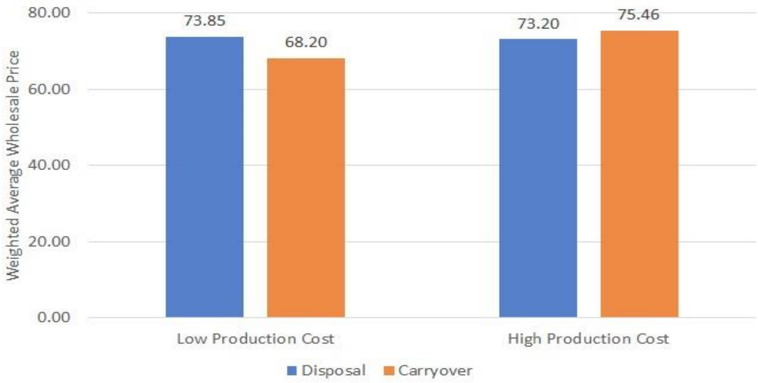

Figure 3.5. Weighted Average Wholesale Prices

Result 4: Retailers over-order in low-profit situations and under-order in high-profit situations.

Figure 6 displays the ordering bias (i.e., the difference between the actual order quantity and the best-response, which is calculated based on the observed wholesale price) response to profit margin for each period under the two inventory commitment options from pooled data. According to Ren and Croson (2013), overconfident individuals have a bias of over-order in the low-profit margin situations, and under-order in the high-profit margin situations, this is consistent with our observations.

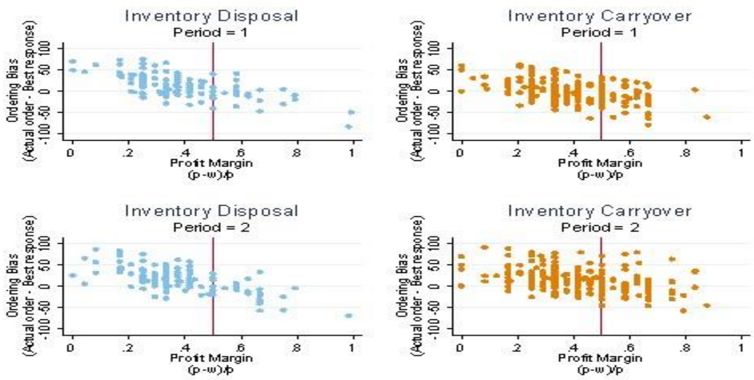

Figure 3.6. Ordering Bias Response to Profit Margin

Result 5: Retailers anchor on past demand.

Recall from model setup in Section 3.1, market demands are independent from each period. Prior behavioral operations management literature has shown that when individuals make decisions across multiple periods, they tend to reference prior realized demands (Bolton and

Katok 2008, Bostian et al. 2008, Wu and Chen 2014). As the retailers make their ordering decision in period 2, they may be influenced by period 1 market demand and take it as a reference point. We conduct a regression analysis, where ordering quantity is the dependent variable and the prior market demand is the independent variable. Table 6 shows that the retailers' ordering quantities in period 2 are significantly correlated with market demand in period 1.

Table 3.6. Regression (o_2 on d_1)

	d_1	p-value	r^2
Low Production Cost	0.311	0.000	0.141
High Production Cost	0.276	0.000	0.110

To further investigate whether the retailers were anchoring on the mean demand, we follow Donohue et al. 2019 by measuring how much the retailers initially anchor on the mean demand (μ) and then adjust a fraction $(1 - \alpha)$ of the optimal adjustment:

$$q = \alpha\mu + (1 - \alpha)q^*$$

where α is the strength of mean anchor, and $(1 - \alpha)$ is the strength of the nominal solution.

Table 3.7. Estimation of Mean Anchoring (α)

	Period 1		Period 2	
	Low Margin	High Margin	Low Margin	High Margin
α	0.781	0.904	0.505	0.434

Table 7 displays the mean anchoring for pooled treatments by profit margins and periods. This is a strong evidence that when making the ordering decisions, the retailers anchor on the mean demand.

Thus far we have identified that the decisions of the suppliers and the retailers were significantly deviated from game theory predictions in most cases. Specifically, the rates of committing to inventory disposal were significantly (all p-value < 0.001) lower than 100% by 62%-72%. In addition, all of the wholesale prices and the ordering quantities are also significantly different from predictions.

It is not uncommon that game theory does not provide good predictions (Donohue et al. 2019). Prior behavioral operations management literature has shown that observed behavior deviates from rational theory often. We explore behavioral explanations in the next section.

3.6 Behavioral Model and Estimation

The main experimental result is that the retailer committed more often to inventory carryover even when committing to disposal is the Nash equilibrium, and the supplier did not correctly respond to the commitment options when setting wholesale prices. We propose a behavioral model to explain these decision biases.

We introduce three assumptions, motivated by observations. First, decisions were noisy and bounded rationality is likely to be the explanation. We model bounded rationality with the popular quantal response equilibrium framework (QRE) (McKelvey and Palfrey 1995). Second, because the ordering quantity in period 2 and the market demand in period 1 are correlated (Result 5), we incorporate anchoring on past demands into the retailer's behavioral model. Third, we find a consistent pull-to-center effect across treatments (Result 4). Ren and Croson (2013) propose overconfidence, where individuals believe their information or their estimates to be more precise than they actually are, as an explanation. Empirical evidence shows that individuals with overconfidence tend to over-order in low-profit margin situations and under-order in high-profit margin situations (Donohue et al. 2019). We introduce overconfidence and use a formulation similar to that of Ren and Croson (2013).

There are other possible explanations for the observed behavioral biases. To be comprehensive, we explore alternative explanations, such as risk aversion, loss aversion, and waste aversion. We find that, empirically, the proposed explanation of anchoring on past demand, together with overconfidence, explains the observed behaviors better than the alternatives. Please see Section 6.6 for details.

3.6.1 The Quantal Response Equilibrium (QRE)

We employ the QRE framework (Su 2008) and find the QRE by backward induction. The model consists of a total of five decisions. We use x for decision variables, and μ for utility functions, with o_2, w_2, o_1, w_1 and opt to index the order quantities, wholesale prices and inventory option decisions. Hence, $x_{opt} \in [0,1]$ be an indicator variable for the decision on the inventory commitment options, with $x_{opt} = 1$ if the retailer commits to inventory carryover, and 0 otherwise. We use γ for bounded rationality parameters, and assume γ can be different for different decisions, let $\gamma_{o2}, \gamma_{w2}, \gamma_{o1}, \gamma_{w1}$ and γ_{opt} be the bounded rationality parameters for order quantities, wholesale prices and inventory commitment decisions respectively. Similar to prior literature, we also assume all the parameters are homogeneous across individuals (Chen et al. 2012, Ho and Zhang 2008, Lim and Ho 2007, Su 2008).

3.6.1.1 Retailer's Order Decision in Period 2

We start with the last possible decision in the game sequence, the retailer's ordering decision in period 2. The expected profit for the retailer, conditioned on inventory commitment, inventory size, and wholesale price, for the ordering decision in period 2 is given by:

$$\pi_{r2}(x_{o2}, x_{w2}, x_{opt}) \ = \ pE(min(x_{o2} + x_{opt}inv, d_2)) - x_{w2}x_{o2}$$

where p is the market price, d_2 is the market demand in period 2, and inv is the realized level of inventory if the retailer committed to inventory carryover. The probability of choosing an ordering quantity in period 2 is given by:

$$P_{o2}(x_{o2}) = \frac{e^{\gamma_{o2}\pi_{r2}(x_{o2})}}{\sum_{x'_{o2}} e^{\gamma_{o2}\pi_{r2}(x'_{o2})}}$$

Similar to Wu and Chen (2014), when $\gamma_{o2} = 0$, the retailer has no intelligence, hence he chooses his ordering quantity among all possible choices with equal probability. Conversely, when γ_{o2} increases and approaches ∞, the retailer always makes the optimal ordering choice to maximize his utility as predicted by game theory.

The expected utility of the retailer in period 2, over ordering decision's quantal response distributions, is given by:

$$E_{r2}(\pi_{r2}(x_{o2}, x_{w2}, x_{opt})) \ = \ \sum_{x_{o2}} P_{o2}(x_{o2})\pi_{r2}(x_{o2}, x_{w2}, x_{opt})$$

3.6.1.2 Supplier's Wholesale Decision in Period 2

By backward induction, the next step is the supplier's wholesale price decision in period 2. The expected profit of the supplier is the wholesale price, and the retailer's expected ordering quantity, given by:

$$\pi_{s2}(x_{w2}) \ = \ x_{w2} \sum_{x_{o2}} (x_{o2}P_{o2})$$

To formulate the supplier's probability of choosing based on the quantal response probability of the subsequent decision, given by:

$$P_{w2}(x_{w2}) = \frac{e^{\gamma_{w2}\pi_{s2}(x_{w2})}}{\sum_{x'_{w2}} e^{\gamma_{w2}\pi_{s2}(x'_{w2})}}$$

The expected utility of the supplier in period 2, over wholesale price decision's quantal response distributions, is given by:

$$E_{s2}(\pi_{s2}(x_{w2})) \ = \ \sum_{x_{w2}} P_{w2}(x_{w2})\pi_{s2}(x_{w2})$$

3.6.1.3 Retailer's Ordering Decision in Period 1

Similarly, the expected profit for the retailer, conditioned on inventory commitment option and wholesale price in period 1, anticipating both the supplier's and the retailer's decisions in period 2, for the ordering decision in period 1 is given by:

$$\pi_r(x_{o1}, x_{w1}, x_{opt})$$
$$= pE(min(x_{o1}, d_1)) - x_{w1}x_{o1} - hx_{opt}max(x_{o1} - d_1, 0)$$
$$+ Er_{r2}(\pi_{r2}(x_{o2}, x_{w2}, x_{opt}))$$

where h is the inventory holding cost if the retailer commits to inventory carryover, and d_1 is the market demand in period 1. Similar to the other decisions, the probability of the retailer choosing an ordering quantity in period 1 is given by:

$$P_{o1}(x_{o1}) = \frac{e^{\gamma_{o1}\pi_r(x_{o1})}}{\sum_{x'_{o1}} e^{\gamma_{o1}\pi_r(x'_{o1})}}$$

The expected utility of the retailer, over ordering decision's quantal response distributions, is given by:

$$E_r(\pi_r(x_{o1})) = \sum_{x_{o1}} P_{o1}(x_{o1})\pi_r(x_{o1})$$

3.6.1.4 Supplier's Wholesale Price in Period 1

The expected profit for the supplier, conditioned on the retailer's inventory commitment option in period 1, expecting retailer's ordering decision, and all period 2 decisions, is given by:

$$\pi_s(x_{w1}) = x_{w1}\sum_{x_{o1}}(x_{o1}P_{o1}) + E_{s2}(x_{w2})$$

The probability of choosing wholesale price in period 1, based on the quantal response probability of the subsequent decision, given by:

$$P_{w1}(x_{w1}, x_{opt}) = \frac{e^{\gamma_{w1}\pi_s(x_{w1})}}{\sum_{x'_{w1}} e^{\gamma_{w1}\pi_s(x'_{w1})}}$$

The expected utility of the supplier, over wholesale price decision's quantal response distributions, is given by:

$$E_s(\pi_s(x_{w1})) = \sum_{x_{w1}} P_{w1}(x_{w1})\pi_s(x_{w1})$$

3.6.1.5 Retailer's Inventory Option

Lastly, the retailer's probability of committing the inventory option decision, based on all supplier's and the retailer's decisions in both periods, given by:

$$P_{opt}\left(x_{opt}\right) = \frac{e^{\gamma_{opt}\pi_r(x_{opt})}}{\sum_{x'_{opt}} e^{\gamma_{opt}\pi_r(x'_{opt})}}$$

The expected utility of the retailer, over inventory commitment option's quantal response distributions, is given by:

$$E_r(\pi_r(x_{opt})) \; = \; \sum_{x_{opt}} P_{opt}(x_{opt})\pi_r(x_{opt})$$

3.6.2 Past Demand Anchoring

Recall from observation result 5 in Section 5 that the retailers were significantly anchoring on realized period 1 demand when making period 2 ordering decisions. We incorporate this effect as a shift in the belief of the *mean* of the demand distribution. Hence, the range of period 2 market demand that the retailer beliefs are given by:

$$A_2^{belief} = A_2 + \alpha d_1$$
$$B_2^{belief} = B_2 + \alpha d_1$$

where A_2 and B_2 are the actual demand range for period 2 and α measures the strength of past demand anchoring.

3.6.3 Overconfidence

We incorporate overconfidence for ordering decisions into the model as a belief of the market demand for the retailer. That is, we measure how much the individuals believe their information or their estimates is more precise than they actually are. In the experiments, the retailers were over-ordered in low-profit margin situations and under-ordered in high-profit margin situations. Hence, we assume that the belief of the demand in the overconfident newsvendor's mind is a mean-preserving but range-reducing transformation of the true market demand $D[A, B]$, mixing the true mean with new demand range $[A^{belief}, B^{belief}]$, similar to Ren and Croson 2013, as follows:

$$A^{belief} = A + \frac{\beta(B - A)}{2}$$
$$B^{belief} = B - \frac{\beta(B - A)}{2}$$

where A and B represent the lower and upper bounds of actual demand, and β is the strength of overconfidence on the belief of the market demand. In the extreme, $\beta = 1$ means that the retailer believes the market demand is constant and equal to its mean. At the other extreme, $\beta = 0$ means that the retailer is unbiased.

3.6.4 Implications on Decision Outcomes

The behavioral model, incorporating bounded rationality, past demand anchoring, and overconfidence, is designed to track and explain the strategic interactions between the supplier and the retailer. In this section, we use numerical analyses to establish a clear picture of how changes in behaviors such as past demand anchoring and overconfidence impact the retailer's decisions.

3.6.4.1 Past Demand Anchoring

Prior literature has shown that when individuals make decisions across multiple stages, they tend to anchor on prior actions (Bolton and Katok 2008, Bostian et al. 2008, Wu and Chen 2014). In our experiments, the retailer's order quantity in period 2 was significantly correlated with realized market demands in period 1. Hence, we incorporate past demand anchoring into our model and find it explains the main finding. We illustrate how past demand anchoring results in different probabilities of committing to the disposal option, all else equal. To show the structural difference, we compute the probability of committing to disposal of the QRE as a function of the level of past demand anchoring, keeping all other behavioral parameters the same. We arbitrarily set $\gamma = 0.002$ for all decisions, but in the same order of magnitude as estimated parameters reported in Table 8 below. We set the overconfidence parameter (β) to zero to isolate the impact of past demand anchoring.

Again, we define α as the past demand anchoring parameter. When $\alpha = 0$, individuals do not anchor on past demand.

Figure 7 illustrates the retailer's probability of committing to disposal for the two treatments as a function of the levels of past demand anchoring. Visual inspection confirms two general patterns. First, the probability of committing to disposal is higher, independent of the level of past demand anchoring, in the low production cost treatment compared to the high production cost treatment, consistent with empirical observations as well as the incentive comparison suggested by game theory.

Secondly and more importantly, the QRE probability of choosing disposal is decreasing in the levels of past demand anchoring. In a QRE with a binary choice, the choice with a higher payoff always has a higher than 50% probability of being chosen, as long as the bounded rationality parameter $\gamma > 0$. We add a line at 50% to indicate when the individual is indifferent between committing to disposal and inventory. When the blue line is above 50%, the individual has incentive to choose to commit to disposal. With a high enough level of past demand anchoring, the probability of choosing disposal drops below 50%. That is, the incentive has reversed and the model explains why individuals are more likely NOT to choose to commit to disposal.

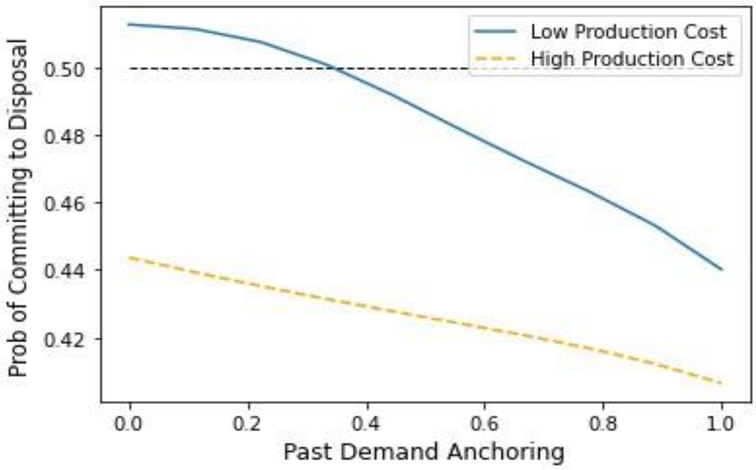

Figure 3.7. Committing to Disposal Response to Past Demand Anchoring

3.6.4.2 Overconfidence

One of the main empirical findings is that the retailers over-order in low-profit margin situations and under-order in high-profit margin situations. Overconfidence can explain this result. Similar to 6.4.1, we use an arbitrary $\gamma = 0.002$ for all the bounded rationality parameters. Similarly, we set past demand anchoring (α) to zero as to isolate the impact of overconfidence. The model (Figure 8) predicts that as the strength of overconfidence increases, the retailer's probability of committing to disposal decreases, and the incentive reverses from committing to disposal to committing to inventory carryover (i.e., less than 50% probability for the blue line) when overconfidence is strong enough.

Both behavioral factors, past demand anchoring and overconfidence, can explain, qualitatively, why individuals have an incentive not to commit to disposal (i.e., less than 50% probability of choosing to do so). As mentioned above, we also find empirical evidence of both behaviors. Hence, we conclude, in this setting, we have two, not one, behavioral factors working in concert to produce a downward bias to the probability of committing to disposal.

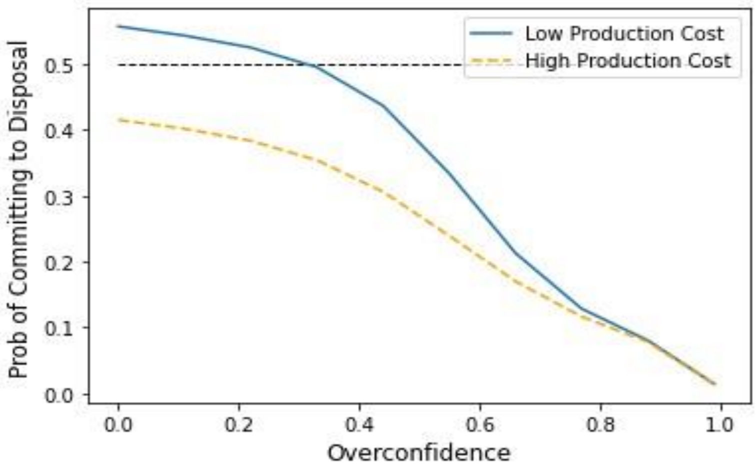

Figure 3.8. Committing to Disposal Response to Overconfidence

3.6.4.3 Wholesale Price Incorrectly Responding to Inventory Commitment

The previous two sections establish how the behavioral model can explain the commitment choice. However, both past demand anchoring and overconfidence directly impact the quantity choices. A natural question is whether the biases of these behaviors impacting the quantity decisions are the sole driver that nudges the incentive from committing to disposal to committing to inventory carryover.

We argue that there is an additional bias, caused by bounded rationality, on the wholesale price that makes further contributions pushing the retailer *away* from committing to disposal. Similar to 6.4.1, we employed numerical analyses to illustrate. We use an arbitrary $\gamma = 0.002$ for all the bounded rationality parameters. We set past demand anchoring (α) and overconfidence (β) to zero as to isolate the impact of bounded rationality. Please see Figure 9 for the illustration.

Game theory suggests that the expected weighted average wholesale price should be lower for committing to disposal compared to committing to inventory carryover. In the low production cost treatment, the behavioral model suggests the reverse is true, and empirical results, also included in the Figure 9, agree with the behavioral model. In the high production cost treatment, both the behavioral model and game theory are consistent with observed decisions.

This is strong evidence that the behavioral model can capture, correctly, the pattern of wholesale price behaviors while game theory fails to do so. Note that a higher weighted average wholesale price, all else equal, can lead to a lower retailer profit as the total costs of inventory is higher. Hence, in the low production cost treatment, the higher weighted average wholesale price changes the incentive and makes the retailer less likely to commit to disposal.

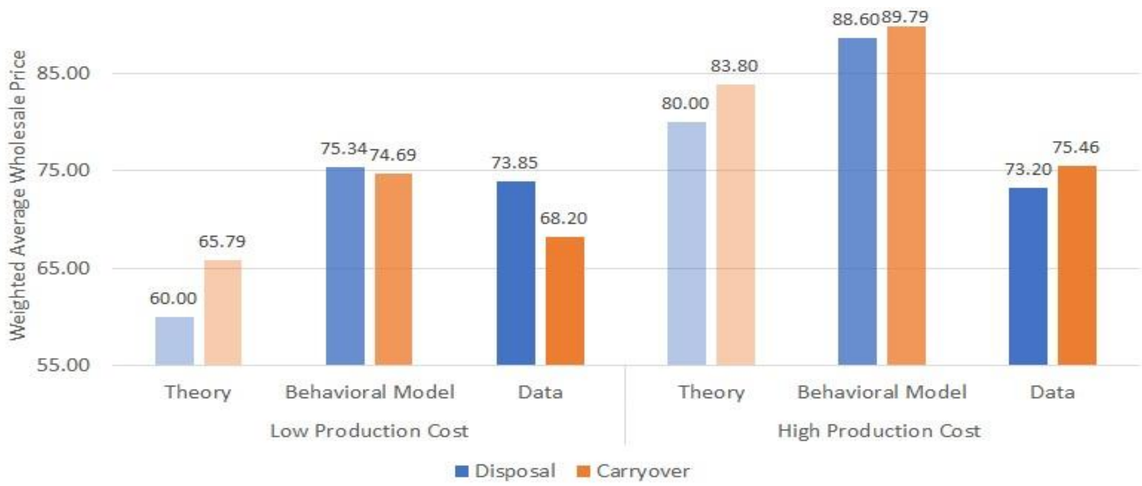

Figure 3.9. Weighted Average Wholesale Price Response to Bounded Rationalities

3.6.5 Model Estimation

We use the maximum log likelihood method to estimate the parameters of the behavioral model. There are 5 bounded rationality parameters $(\gamma_{o2}, \gamma_{w2}, \gamma_{o1}, \gamma_{w1}, \gamma_{opt})$ representing the five decisions (2 ordering decisions, 2 wholesale price decisions, and inventory commitment decision) and two behavioral parameters (α, β) representing the strength of past demand anchoring and overconfidence. The log likelihood function is the sum of the log of the probabilities of each decision, given by:

$$LL(\theta) = \sum (log(P_{o2}(x_{o2})) + log(P_{w2}(x_{w2})) + log(P_{o1}(x_{o1})) + log(P_{w1}(x_{w1})) + log(P_{opt}(x_{opt})))$$

where $\theta = \gamma_{o2}, \gamma_{w2}, \gamma_{o1}, \gamma_{w1}, \gamma_{opt}, \alpha, \beta$ are the behavioral parameters.

3.6.5.1 Estimation Results

Table 8 summarizes the estimation results for each treatment. We use log likelihood ratio tests to examine whether the parameters are significantly different from zero.

Table 3.8: Model Estimation Results

Parameters	Low Production Cost	High Production Cost
γ_{o2}: o_2 bounded rationality	0.0014 (0.000)	0.0007 (0.000)
γ_{w2}: w_2 bounded rationality	0.0021 (0.000)	0.0005 (0.000)
γ_{o1}: o_1 bounded rationality	0.0012 (0.000)	0.0011 (0.000)
γ_{w1}: w_1 bounded rationality	0.0008 (0.000)	0.0005 (0.000)

γ_{opt}: $option$ bounded rationality	0.0039 (0.001)	0.0020 (0.000)
α: past demand anchoring	0.1809 (0.000)	0.2750 (0.001)
β: overconfidence	0.1216 (0.000)	0.1072 (0.032)
Note: p-value is listed in parentheses.		

Result 1: Individuals anchor on past demand.

The past demand anchoring (α) parameters are positive and highly significant (p-value < 0.001) in both treatments. This is strong evidence that individuals anchor on realized market demand in the past when making current ordering decisions. In addition, the retailers anchor significantly (p-value < 0.001) more on the past demand in the high production cost treatment compared to low production cost treatment.

Result 2: Individuals are overconfident when estimating the market demand.

The overconfidence (β) parameters are positive and significant (p-value < 0.05). The β parameters are roughly 10% which can be interpreted as the beliefs of the demand range shrinking by about 10%.

We conclude that individuals anchor on past demand and are overconfident, consistent with past literature. More importantly, both contribute to the reduction of the incentive to commit to disposal.

3.6.6 Alternative Behavioral Explanations

While we present strong empirical evidence, by the use of a structural model, of past demand anchoring and overconfidence, it is important to rule out alternative explanations.

Following Schweitzer and Cachon (2000), we consider risk and loss aversion. Experimental results suggest that individuals are prone not to commit to disposal. Hence, waste aversion seems like a natural possibility. For completeness, we also consider its opposite, stockout aversion. In addition, several studies have noted that fairness concern is a prominent social motivation in supply chain settings (Cui et al. 2007, Katok and Pavlov 2013).

We formally tested these alternative behavioral explanations. We create alternate models by integrating these behavioral factors into the quantal response equilibrium framework. Since these models are not nested with our main model, we use AIC as the model selection criteria. The results are reported in Table 9.

Table 3.9. AIC Comparison

	Low Production Cost Treatment	High Production Cost Treatment	Explain Pull to Center?	Explain Bias in not Committing to Disposal?
Main Model	3686.40	3715.30	Yes	Yes
Noise Only	3714.31	3736.48	No	No
Stockout Aversion	3712.94	3736.81	No	Yes
Risk Aversion (CARA)	3705.21	3738.48	No	Yes
Loss Aversion	3695.42	3731.28	No	Yes
Waste Aversion	3716.31	3738.48	No	No
Fairness Concerns	3716.31	3738.48	No	Yes

- Noise Only: bounded rationality only.
- Stockout aversion: $u_r = E\pi_r - \alpha \int_q^{\infty} f(x)(x-q)d_x$, where α is the stockout aversion parameter.
- Constant absolute risk aversion (CARA): $u_r = \frac{1-e^{-rE\pi_r}}{r}$, where r is the risk aversion parameter[12].
- Loss aversion: $u_r = \begin{cases} E\pi_r, & if\ \pi_r \geq 0 \\ \lambda E\pi_r, & if\ \pi_r < 0 \end{cases}$, where λ is the loss aversion parameter.
- Waste aversion: $u_r = E\pi_r - t\int_0^q f(x)(q-x)d_x$, where t is the waste aversion parameter.
- Fairness: $u_r = \pi_r - \theta max(\pi_s - \pi_r, 0)$, where θ is the fairness concerns.

As one can see, the main model is better than all the alternatives in both treatments. In addition, it is the only model that can explain both pull-to-center and the bias in not committing to disposal.

3.7 Discussion and Conclusion

This paper investigates the role of *strategic disposal* in a two-period supplier-retailer setting where demand is stochastic. We are the first to study the strategic consideration of whether to hold inventory or dispose of unsold units when demand is stochastic, a departure from the strategic inventory literature. We employ a combination of game theory, human-subject experiments, and behavioral modeling.

We find that individuals under-commit to disposal and we verify two behavioral drivers for this bias. First, individuals anchor on past realized demand when making order decisions.

[12] There are multiple formulations of risk aversion. We choose the CARA formulation as it is common in operations management research (Li et al. 2020).

We show that as the strength of past demand anchoring increases, the probability of committing to inventory disposal decreases.

Second, our experimental results show that the retailers' decisions are affected by a "pull-to-center" effect, similar to prior newsvendor setting experiments (Bostian et al. 2008). We incorporate overconfidence into our behavioral model, and find it explains the data. We show that when the strength of overconfidence increases, the probability of committing to inventory disposal also decreases. We conclude that the bias of not committing to disposal is driven by both past demand anchoring and overconfidence.

Recently, some corporations are criticized for disposing of unsold inventory as the practice is deemed wasteful and has a negative impact on the environment (Rockstrom et al. 2009), and opposite to social responsibility and working towards a sustainable future. For example, according to Fortune, Amazon is slammed for destroying millions of unsold items in Britain and France warehouses because the economic value to sell those products are less than the costs to hold and process them (Hamilton, 2019). Also, according to the Wall Street Journal, American dairy farmers poured out more than 43 million gallons of milk in landfill in 2016 due to surplus supply, it was the most food wasted in at least the last 16 years (Gee 2016). Moreover, British luxury fashion brand Burberry burned over $37 million worth of products in 2017 to protect its brand from dropping in price (Dalton 2018). While ethical considerations are beyond the scope of this paper, we do conclude that the incentive to dispose of unsold inventory can be mitigated by behavioral factors (i.e., past demand anchoring and overconfidence). Ethical considerations, intuitive, should further reduce the practice of disposal. Hence, these anecdotal examples may be more the exception than the general rule.

The study is not without limitations. As one of the first studies to examine the effect of strategic disposal via a behavioral game theory approach, we introduce a simple two-period newsvendor setting to demonstrate the key strategic interactions. Hence, some nuances in real world scenarios are not fully explored. For example, we limit the study to focus on one supplier-one retailer setting where multiple suppliers and retailers networks are common in practice. Another example is that we assume the supplier is able to fulfill all orders where the supply chain disruption might exist due to uncertainty. We also assume a complete information game where all the relevant parameters such as market demand, market price, inventory holding cost, and size of inventory are known to all players when substantial asymmetric information may exist.

The limitations of the study suggest future extensions, along two directions. The first is to study how possible supply chain disruption affects the strategic interactions between the supplier and the retailer. The second is to investigate how setting characteristics such as asymmetry of demand information and visibility of level of inventory, can affect our conclusions. There are a wide range of untested possibilities. Inventory sharing systems, which reduce the stockout risk, is one example. Different forms of contract, such as revenue sharing or quantity discount, may enhance the supply chain efficiency. Finally, field tests and empirical studies can also provide righteous support between our results and real-world practices.

Chapter 4

Strategic Disposal or Strategic Carryover? A Theoretical Study of Decision-Making in the Presence of Supply Disruption Risk

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4.1 Introduction

In March 2011, nearly all Japanese carmakers shut down their factories either because of the potential nuclear meltdown or because of the earthquake and tsunami. The disaster in Japan soon caused a butterfly effect to the global auto industry, which soon was coping with parts shortages including the U.S., South America, and Europe (Muller 2011). More recently, during the COVID-19 Pandemic, about 93% of people around the world live in countries that have shut down their global logistics and closed their borders in order to reduce the separation speed of the virus (Shoichet 2020). Virtually all globalization companies took a major hit and were forced to close their factories because of the shortage of supply on raw materials or equipment. How to handle the disruption risk has become a critical issue that modern managers must face in nowadays business (Gurnani et al. 2014), and the assessment on supply chain vulnerability has become an important factor in the supply chain coordination (Yu et al. 2009).

In the traditional wholesale price contract (Spengler 1950), a retailer orders a product from a supplier and sells it to a market with an exogenous stochastic demand at an exogenous market price. Since the order quantity is placed before the actual market demand is realized, sometimes the retailer may over order, other times, he may under order. While complying with his operations strategy, the retailer must balance the costs of overstocking against the costs of understocking before making his ordering decision. If the retailer aims on a cost saving strategy, he probably will order less, and prefer understocking more than overstocking. Although overstocking may cause potential waste because of the uncertainty of the market demand, it is not an uncommon activity for many retailers in practice nowadays. Study shows that about 21% to 43% shoppers will actually go to another store if they find out the products are stockout at their desired store. Those abandoned transactions mean $40 million lost sales in a billion-dollar retailer store (Corsten and Gruen 2004). In fact, if the retailer has a customer oriental focus strategy or has a concern about his reputation, he probably prefers overstocking more than understocking.

Although the optima ordering solution (refers as critical fractile) to the newsvendor problem have been known since Arrow et al (1951). But numerous studies have shown individuals are likely to suffer from varies decision biases, such as pull to center effect, risk/loss aversion, and stockout aversion (Schweitzer and Cachon 2000, Bostian et al 2008, Katok and Wu 2009), which may cause them systematic deviate from making optimal ordering decision. There is plenty of evidence to suggest that many newsvendor interactions in nowadays business practice take place in multi-period settings with some supply chain distribution risks.

The key issue we focus on in this paper is to investigate the interactions between the supplier, who is exposed under possible supply disruption risk, and the retailer, who has an option to either dispose or carryover his inventory, in a two-period newsvendor setting. Although, high level of waste is considered problematic from multiple perspectives, as it has a negative impact on environment, economic, and social (Rockstrom et al. 2009), strategic wasting (or disposal) is often used in practice to hedge high level inventory cost or to increase its market power. According to the Wall Street Journal, American dairy farmers poured out more than 43 million gallons of milk in landfill in 2016 due to surplus supply, it was the most food wasted in at least the last 16 years (Gee 2016). The idea of dumping milk is intuitive. If the farmers want to keep the milk price up, the easiest way is to reduce their supply.

Given the extensive theoretical works in newsvendor are in a one-period supply chain setting without possible supply chain distribution, and the market demand does not vary across different periods. It is not clear that theoretically predictions are behaviorally consistent in multi-period interactions. Especially, prior studies may not be able to capture the behavioral change that the supplier is exposed to under production risks and the retailer has the option to choose the commitment on either to inventory disposal or to inventory carryover. Depending on the inventory holding cost and the probability of the supply chain distribution risks, strategic disposal may become an advantage tool for retailers, in order to achieve higher profit. Conversely, the stockout aversion retailer acts more aggressively in order quantity and may exhibit disutility of stockout. The more sensitive the retailer is to the dis-utility of stockout, the more he is choosing the inventory carryover option. Such a phenomenon leads to wrong choice of option, which damages the profits not only of the retailer, but also of the supplier and the total supply chain.

In this paper, we first provide theoretical predictions for a two-period newsvendor supply chain. In the special case in which the supply disruption risk is zero, the supplier will offer a lower weighted average wholesale price if the retailer commits to an inventory disposal strategy. Hence, a risk-neutral retailer will always choose to commit to inventory disposal to maximize his profit. As the probability of the supply disruption risk increases, the retailer will switch to the inventory carryover strategy.

Having theoretically analyzed the retailer’s inventory option choice, we test the theory with numerical analyses. Our analyses were implemented with two questions in mind. First, how does retailer inventory choice behavior vary under the risk of supply disruption in different market demands? Second, how does the likelihood of the supply disruption risk impact and influence the supply and the retailer decisions?

To study these research questions, we include three different market demand scenarios: (1) same demand distribution across two periods, (2) decrease demand distribution, and (3) increase demand distribution, and two levels of supply disruption risks: (1) high supply disruption risk, (2) low supply disruption risk. The three demand treatments allow us to investigate the first research question, and high and low supply disruption risks allow us to investigate the second research question.

This paper is organized as follows. Section 2 summarizes the related theoretical literature on the strategic inventory and strategic disposal, supply disruption risk, and newsvendor models. Section 3 describes the model and research questions, §4 further explores the extensions of the model. Lastly, we conclude the paper with a discussion of the research and managerial implications, some limitations of this paper, and future extension of this work in §5.

4.2 Literature Review

Three streams of literature are relevant for our study: inventory disposal and inventory carryover and, literature of supply disruption risk, and behavioral economics literature about the newsvendor problem.

The first literature stream investigates the inventory disposal and inventory carryover. Balancing the cost of disposal is important to the sustainability of a retailer. Sociologists argue that no individual prefers to waste, there are many negative consequences of wasting that impact the environment, economic, and social (Rockstrom et al., 2009). In nature, there is a psychological impact in people's minds that they tend to feel bad or guilty about wasting (Evans 2012). Research also suggests that consumers have disutility of wasting if a purchase that will go unconsumed (Bolton and Alba, 2012). However, it is not uncommon in business that firms use strategic disposal (waste) as a competitor advantage tool in order to gain market power or to smooth the competition. According to Fortune, Amazon was slammed for destroying millions of unsold items in the German warehouse because the economic value to sell those products are less than the costs to hold and process them (Meyer, 2018).

Arkes and Blumer (1985) were the first to show waste as an explanation for the sunk-cost bias. In this paper, by allowing the retailer to choose between inventory carryover or commit to dispose of any unsold products at the end of period 1, we examine a behavioral explanation for those who choose inventory carryover option, a particular form of stockout aversion.

Conversely, Anand et al. (2008) show that under certain conditions, a retailer can use strategic inventory as a competitive tool in a multi-period supply chain in order to force the supplier to lower the wholesale price in a later period. Although the strategic inventory is carried by the retailer, it not only benefits the retailer, it may also benefit the supplier and the total supply chain, because of the reduction in the degree of double marginalization. Recent experimental studies have shown that the retailer uses strategic inventory as theory prediction in a two-period supply chain setting, but sometimes, he tends to show an under-responding bias (Hartwig et al. 2015, Lang and Chen 2021). Most research in this stream of the literature assumes deterministic demand with the price to be linear in the selling quantity. In this paper, we use a newsvendor setting with stochastic demand and possibility of supply disruption risk. Worth noting is that once demand is stochastic, inventory levels also become stochastic. Hence, our definition of "inventory use" is different from this stream of literature. We define "inventory use" as whether the retailer is committing to carry inventory.

The second literature stream appeals to various forms of supply disruption risk to describe behavioral effects in different settings. Tomlin (2006) studies mitigation and contingency strategies for managing supply chain disruption risks. They show that mixed mitigation strategy (partial sourcing from the reliable supplier and carrying inventory) can be optimal in a single-product two suppliers setting. Wu et al. (2007) presents a network-based modeling methodology to determine how changes or disruptions propagate in supply chains and how those changes or disruptions affect the supply chain system. Yu et al. (2009) focus on evaluating the impacts of supply disruption risks on the choice between the single and dual sourcing methods in a two-stage supply chain with a non-stationary and price-sensitive demand.

Not many papers have focused on newsvendor problem supply disruption risk with market demand changes across multiple periods. In this paper, we particularly focus on the decision alignment between the retailer and the supplier in terms of achieving coordination when supply disruption risk exists, and use a behavioral model to explain the strategic interaction across two periods.

The last stream investigates the possible behavioral impact on the newsvendor problem. There are two critical findings from the standard newsvendor game literature: (1) retailer optimal orders quantity is $F(q) = (p - w)/p$, which is known as the critical fractile (Arrow et al. 1951), and (2) comparing with the supply chain which has been owned by a single player, decentralized two players newsvendor channel efficiency is at 75%. Prior experimental studies have shown that individuals do not follow game theory predictions. When individuals make decisions to maximize their profit, the two central findings from the experimental work are that (1) they lack the ability to do so, because they are being bounded rational, and (2) they mistakenly include additional utilities, so their decisions and response are changed.

Schweitzer and Cachon (2000) conduct the first laboratory study of the newsvendor problem. They show that retailers often underordered in high profit margin condition, and over ordered in low profit margin condition. The preference on over or under order cannot be explained exclusively by risk aversion, risk seeking, loss aversion, waste aversion, stockout aversion, or underestimation of opportunity costs. Prospect Theory preference can explain some but not all of the data. They suggest additional techniques are required to improve decision making.

Additional behavioral newsvendor experiments have shown that people's behavior improves over time via dynamic learning. But order on anchoring biases are still observed (Bolton and Katok 2008, Bostian et al. 2008). Most newsvendor experimental studies use a single-period setting, we extend the literature and study the interaction effect in a two-period newsvendor with possible supply disruption setting.

This paper fills the gap in the literature by employing a combination of game theory and numerical analysis to explain the possible decision biases in the two-period newsvendor setting, where the retailer has an option to choose inventory carryover or disposal in different market demand distribution and the supplier faces possible disruption.

4.3 Model Setting and Game Theoretical Prediction

In this section, we introduce our main model, which is based on the two-period newsvendor game and also outlines the results for the benchmark model, where the supplier does not have disruption risk.

4.3.1 Benchmark Model: Two-Period Model Without Supply Disruption Risk

Consider a two-period vertical supply chain which consists of a supplier (she) and a retailer (he). The supplier provides the retailer with a product that the retailer sells to the market. Actual market demand is realized after the retailer makes the order quantity decision in each period.

The retailer has an option to choose how to process his inventory at the end of period 1 before the supplier sets the wholesale price. He can either commit to dispose of them or carryover them to Period 2. Without losing generality, any unsold products will be lost with zero salvage value at the end of period 2. Market price and inventory holding cost are common knowledge.

If the retailer chooses the commit to the inventory disposal, the supplier sets the wholesale price (w) and the retailer sets ordering quantity (o). Conversely, if the retailer chooses the inventory carryover option, the supplier sets the wholesale price (w_1) and the retailer sets ordering quantity (o_1), also the retailer pays holding cost (h) for every product that is unsold in period 1. In period 2, after observing the retailer's inventory level (i), the supplier sets the wholesale price (w_2) and the retailer sets ordering quantity (o_2).

The following table summarizes the order of events for the two settings (commit to dispose, and inventory carryover).

Table 4.1. Order of Events of Two-Period Newsvendor Game

Stage 1	Retailer chooses inventory disposal or carryover	
	Commit to Dispose	Inventory Carryover
Stage 2	Supplier sets wholesale price for period 1	
Stage 3	Retailer sets ordering quantity for period 1	
	Unsold products lost	Unsold products become inventory, and Retailer pays inventory holding cost
Stage 4	Supplier sets wholesale price for period 2	After observing Retailer's inventory level, Supplier sets wholesale price for period 2
Stage 5	Retailer sets ordering quantity for period 2	

The expected profits of the supplier and the retailer are as follows:

$$\pi_s = w_1 o_1 + w_2 o_2$$

$$\pi_r^{\text{Disposal}} = pEmin(o_1, d_1) - w_1 o_1 + pEmin(o_2, d_2) - w_2 o_2$$

$$\pi_r^{Carryover} = pEmin(o_1, d_1) - hEmax(o_1 - d_1, 0) - w_1 o_1 + pEmin(o_2 + i, d_2) - w_2 o_2$$

where market price (p) and inventory holding cost (h) are exogenous. To make this analysis tractable, we assume that the market demand (d) in each period is a random variable following uniform distribution between [0, 1] (Li et al. 2014).

Theory predicts that the retailer should always commit to the disposal option because of the lower weighted average wholesale price set by the supplier compared to choosing the inventory carryover option. Conversely, the supplier prefers the retailer to choose the inventory carryover option if it is feasible to carry, because she can set a higher weighted average wholesale price, and the total supply chain efficiency is higher compared with if the retailer chooses inventory disposal option because there is no potential loss in sales in period 1.

4.3.2 Effect of Supply Disruption Risk

We extend the model by adding supply disruption risk (r) to the supplier. Hence, there is a probability that the supplier cannot supply the product in period 2. The probability of supply disruption risk is also known to the retailer. Our model is relevant to many settings in practice where supply disruption often happens in nowadays globalization supply chain.

In the supply disruption model, the probability of supply disruption risk (r) is estimated and revealed to the supplier and the retailer at the beginning of the game. The rest of the events are identical to the two-period newsvendor game.

The following table summarizes the order of events for the two settings (commit to dispose, and inventory carryover).

Table 4.2. Order of Events of Supply Disruption Game

<table>
<tr><td>Stage 1</td><td colspan="2">The probability of supply disruption risk is estimated and reveal to everyone</td></tr>
<tr><td>Stage 2</td><td colspan="2">Retailer chooses inventory disposal or carryover</td></tr>
<tr><td></td><td>Commit to Dispose</td><td>Inventory Carryover</td></tr>
<tr><td>Stage 3</td><td colspan="2">Supplier sets wholesale price for period 1</td></tr>
<tr><td>Stage 4</td><td colspan="2">Retailer sets ordering quantity for period 1</td></tr>
<tr><td></td><td>Unsold products lost</td><td>Unsold products become inventory, and Retailer pays inventory holding cost</td></tr>
<tr><td>Stage 5</td><td>Supplier sets wholesale price for period 2</td><td>After observing Retailer’s inventory level, Supplier sets wholesale price for period 2</td></tr>
<tr><td>Stage 6</td><td colspan="2">Retailer sets ordering quantity for period 2</td></tr>
</table>

The expected profits of the supplier and the retailer are as follows:

$$\pi_s = w_1 o_1 + (1-r) w_2 o_2$$

$$\pi_r^{\text{Disposal}} = pEmin(o_1, d_1) - w_1 o_1 + (1-r)(pEmin(o_2, d_2) - w_2 o_2)$$

$$\pi_r^{Carryover} = pEmin(o_1, d_1) - hEmax(o_1 - d_1, 0) - w_1 o_1 + (1-r)(pEmin(o_2 + i, d_2) - w_2 o_2) + r\big(pEmin(i, d_2)\big)$$

where the probability of supply disruption risk (r) is exogenous.

4.3.3 Theoretical Analysis

We characterize the subgame-perfect Nash equilibriums of the game under the “commit to dispose” and the “inventory carryover” settings, and summarize the results in Table 3. Please see appendix A for associating proofs.

Table 4.3. Game Theory Predictions

	Disposal	Inventory Carryover
Wholesale price $\{w_1, w_2\}$	$\frac{p}{2}, \frac{p}{2}$	$\frac{16h^2(1+3r)-4h(r-1)(7r-3)p+2\big(23+r\big(59+r(13+r)\big)\big)p^2-\sqrt{2}\mathrm{x}}{2(7+5r)^2 p}$, $\frac{1}{4}\left(2-\frac{y^2}{(3+r)^2p^2}\right)p$
Retailer order $\{o_1, o_2\}$	$\frac{1}{2}, \frac{1}{2}$	$\frac{\mathrm{y}}{(3+r)p}, (\frac{1}{2}-\frac{y^2}{4(3+r)^2p^2})$
Inventory I	-	$\frac{y^2}{2(3+r)^2p^2}$

where $x = \sqrt{(-4h + 5p - 12hr - 6pr + pr^2)^2(8h^2 + 8hp + 9p^2 - 8hpr + p^2r + 2p^2r^2)}$

and $y = -4h + p(-1 + r) +$

$$\sqrt{\frac{-8hp(-1+r)(67+r(34+11r))+16h^2(37+r(30+13r))+p^2(673+r(444+r(310+r(92+17r))))+4\sqrt{2}(3+r)x}{(7+5r)^2}}$$

Table 4.4. Optimal Inventory Option

	Condition	Optimal Inventory Option
Constant Demand	$r \leq 51.03\%$	Commit to Disposal

From the optimal inventory option choice results in Table 4, as the probability of supply disruption risk (r) reaches the threshold point, the optimal inventory strategy for the retailer switch from commit to disposal to carryover. In one extreme case, if the retailer knows that there is a 100% probability that the supplier will be disrupted in period 2 (i.e., $r = 1$), he will definitely choose the inventory carryover option, and stack as much inventory he needs for period 2. Conversely, if the retailer knows that there is a 0% probability that the supplier will be disrupted in period 2 (i.e., $r = 0$), he will commit to the disposal option in order to maximize his total profit.

Next, we analyze the impact of r on the profits of the supplier, the retailer, and the supply chain.

4.4 Extensions: Supply Disruption Risk with Changing Demands

Since the market demands in practices are not always constant across periods. We now consider extensions of the supply disruption model to further investigate the effect of supply disruption risk when market demand in period 2 either is decreasing or increasing.

Consider again the two-period newsvendor setting with the presence of supply disruption risk, but suppose market demand across periods are no longer identical uniformly distributed. For example, the range of the market demand in period 2 may be decreasing/increasing compared with period 1.

To investigate how changing demands affect the interactions of the supplier and the retailer, we study two scenario cases. In the first scenario, we assume the range of the market demand in period 2 is decreasing while we assume the range of the market demand in period 2 is increasing in the second scenario.

Employing the methodology developed in section 4.3, the optimal inventory option for the retailer is shown in Table 5.

Table 4.5. Optimal Inventory Option (Demand Changing)

	Condition	Optimal Inventory Option
Decreasing Demand	$r \leq 7.9\%$	Commit to Disposal
Increasing Demand	$r \leq 34.75\%$	Commit to Disposal

Intuitively, when the range of the market demand is decreasing, the retailer has more incentive to choose the inventory carryover option in the presence of supply disruption risk. Hence, the probability threshold that triggers the retailer switching from commit to the disposal option to the inventory carryover option is lower compared with the constant market demand case. One surprise finding is that when the range of the market demand is increasing in period 2, the trigger point is also lower compared with the constant market demand case.

4.5 Conclusion

Based on the practice experience that suppliers often do not have the capacity to guarantee disruption risk free supply chain, we examine how the probability of supply disruption risk affects the behavior of a supplier and a retailer under a wholesale price contract. In particular, we examine how the probability of supply disruption risk affects the retailer's inventory decision and the supplier's wholesale pricing decisions. While much of the literature on supply chain has focused on the importance of strategic inventory, our study addresses a previously unrecognized problem that is a form of risk uncertainty.

In a disruption risk free supply chain, the retailer does not need to hold any inventory and worry about the possibility of supply disruption in the future. When the supply disruption risk exists in the supply chain, depending on the disruption probability, the retailer needs to respond to the risk by switching his inventory choice from disposal to carryover. When the retailer chooses the inventory carryover option, the retailer can hold the inventory as a competitor advantage tool to put downward pressure on the supplier's future wholesale price. This weakens the retailer's commitment power, because the level of the inventory is depending on the realized market demand. However, because the retailer chooses to carry inventory over to the next period, the supplier will strategically set a higher wholesale price at the beginning in order to outweigh the benefit of carryover and a lower wholesale price in the later period. Consequently, the retailer will have a higher weight average cost that results in a lower profit compared if committing to the disposal option. As the probability of supply disruption risk increases, the retailer will prefer the inventory carryover option even more. In a sense, the retailer will earn less profit even though he cannot prevent it.

The presence of supply disruption risk leads to several somewhat unexpected findings. First, although it is intuitive to expect that the higher probability of supply disruption risk would lead to higher inventory carryover, we find that this is true even in changing demand conditions. However, the probability threshold in equilibrium that pushes the retailer switches from commit to disposal option to inventory carryover option differs when demand is changing in period 2. The probability threshold is the lowest when demand is decreasing, and highest when demand is constant. When demand is increasing, the probability threshold is in between the other two conditions. Second, regardless of what is the probability of supply disruption risk, the supplier always prefers the retailer to choose the inventory carryover option. Although strategic inventory will weaken the overall market power of the supplier, she can strategically outweigh the benefits by setting a higher wholesale price at the beginning.

By focusing on a simple model between a single supplier and a single retailer in a two-period supply chain with stochastic demands, we have demonstrated how the presence of supply disruption risk alters the interactions between the supplier and the retailer under dynamic wholesale price contract. Consequently, the retailer will respond to the probability of supply disruption by switching his optimal inventory strategy from commit to disposal to inventory carryover, but he does not necessarily benefit from the inventory choice changes. Of course, there are many other implications of supply disruption risk that will affect the strategy interactions of the supplier and the retailer. Our paper highlights the need to balance any direct effects from the presence of supply disruption risk against the preference of committing to the inventory disposal.

To avoid unnecessary complication, we have restricted our attention to wholesale price contracts, but it would be of interest to investigate more sophisticated contracts, such as quantity discount contracts or two-part tariff contracts. Prior experimental studies have shown that individuals do not follow game theory predictions. When individuals make decisions to maximize their profit, the two central findings from the experimental work are that (1) they lack ability to do so, because they are being bounded rational, and (2) they mistakenly include additional utilities, so their decisions and response are changed. To investigate what would be the supplier’s and the retailer’s actual responses in the presence of supply disruption risk, a series of controlled laboratory experiments may be conducted as the extension of this research.

Appendix A

PROOF OF THE RESULTS IN CHAPTER 2

Appendix A1: Theoretical Predictions

	No-Inventory Model	Strategic Inventory Model
Wholesale price $\{w_1, w_2\}$	$\{\frac{5d-c}{10}, \frac{5d-c}{10}\}$	$\{\frac{355d-50h-47c}{710}, \frac{71d+110h-67c}{142}\}$
Supplier selling $\{z_{s1}, z_{s2}\}$	$\{\frac{5d-7c}{10\alpha}, \frac{5d-7c}{10\alpha}\}$	$\{\frac{1065d-50h-1467c}{2130\alpha}, \frac{213d+110h-351c}{426\alpha}\}$
Retailer order $\{r_{o1}, r_{o2}\}$	$\{\frac{2c}{5\alpha}, \frac{2c}{5\alpha}\}$	$\{\frac{2526c-2600h}{3195\alpha}, \frac{150c+220h}{639\alpha}\}$
Retailer selling $\{z_{r1}, z_{r2}\}$	$\{\frac{2c}{5\alpha}, \frac{2c}{5\alpha}\}$	$\{\frac{402c+50h}{1065\alpha}, \frac{138c-110h}{213\alpha}\}$
Inventory I	0	$\frac{264c-550h}{639\alpha}$
Market price $\{p_1, p_2\}$	$\{\frac{5d+3c}{10}, \frac{5d+3c}{10}\}$	$\{\frac{1065d-50h+663c}{2130}, \frac{213d+110h+75c}{426}\}$
Retailer profit Π_r	$\frac{8c^2}{25\alpha}$	$\frac{447624c^2-395400ch+456250h^2}{1134225\alpha}$
Supplier profit Π_s	$\frac{9c^2-10cd+5d^2}{10\alpha}$	$\frac{6327c^2-6390cd-2400ch+3195d^2+2500h^2}{6390\alpha}$
Supply chain profit Π_{SC}	$\frac{61c^2-50cd+25d^2}{50\alpha}$	$\frac{1047111c^2-756150cd-547600ch+378075d^2+600000h^2}{756150\alpha}$

Appendix A2: Proof

Proposition 1: Retailer carries strategic inventory for $h \leq 0.48c$.

Because of $I = (264c - 550h)/639\alpha \geq 0$, and α is the price sensitivity to quantity ($\alpha \geq 0$). Hence, for $(264c - 550h) \geq 0$ to be true, $h \leq 0.48c$.

Result 2: Weighted average wholesale price is lower in the strategic inventory model than the no-inventory model.

$$w_{weighted}^{SI} = \frac{-30831c^2-625(71d-98h)h+35c(2769d+95h)}{710(273c-125h)}$$

$$w_{weighted}^{NI} = \frac{(5d-c)}{25\alpha}$$

Because of $c \geq 0, d \geq 0, h \geq 0, \alpha \geq 0$, and $w_{weighted}^{NI} \geq w_{weighted}^{SI}$ for $h \leq 0.48c$. Hence, weighted average wholesale price is lower in the strategic inventory model than the no-inventory model for $h \leq 0.48c$.

Proposition 2: Supply chain efficiency is higher in the strategic inventory model than the noinventory model, $\Pi_{SC}^{I} \geq \Pi_{SC}^{NI}$ for $h \leq \frac{649}{1500}c \approx 0.43c$.

$$\Pi_{SC}^{SI} = \frac{1047111c^2-756150cd+378075d^2-547600ch+600000h^2}{756150\alpha}$$

$$\Pi_{SC}^{NI} = \frac{61c^2-50cd+25d^2}{50\alpha}$$

Because of $c \geq 0, d \geq 0, h \geq 0, \alpha \geq 0$, and $\Pi_{SC}^{SI} \geq \Pi_{SC}^{NO}$ for $h \leq \frac{649}{1500}c \approx 0.43c$. Hence, Supply chain efficiency is higher in the strategic inventory model than the no-inventory model for $h \leq \frac{649}{1500}c \approx 0.43c$.

Appendix A3: Experiment Screenshots

Instruction-Background Information

This is an experiment in the economics of decision-making. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment. You have already earned US$0.25 show-up fee for participating. You will earn *experimental dollars* during the experiments, and experimental dollars will be converted to US dollars at the end of the experiment with the following exchange rate.

30,000 experimental dollars = US$1

You will receive the show up fee ($0.25) and any additional earnings ONLY if you finish the experiment.

In this experiment, there are two players: Supplier and Retailer. During the experiment, you will be randomly assigned to be either the Supplier or the Retailer. After two practice rounds, you will be randomly paired up with another human player and form a 1 Supplier - 1 Retailer group. You will interact with that person for 2 decision periods.

Supplier

In each period, the Supplier makes profit by (1) selling the product to the Retailer and/or (2) directly selling the same product to the customers via a direct channel at a per unit selling cost. The Supplier decides the wholesale price, and its direct selling quantity. When the Supplier sells the product to the customers, the Supplier sells at a Market Price.

Retailer

In each period, the Retailer decides the order quantity and selling quantity. The Retailer pays the Wholesale Price for each product ordered, and receives the Market Price for each product sold to the customers.

The Retailer can order MORE than she sells in the first period. If the Retailer orders more than she sells, the difference is referred to as Inventory. The Retailer pays a Holding Cost for each unit of Inventory held at the end of the first period. In the second period, the retailer must sell everything and pay for the 1st period's inventory purchase cost.

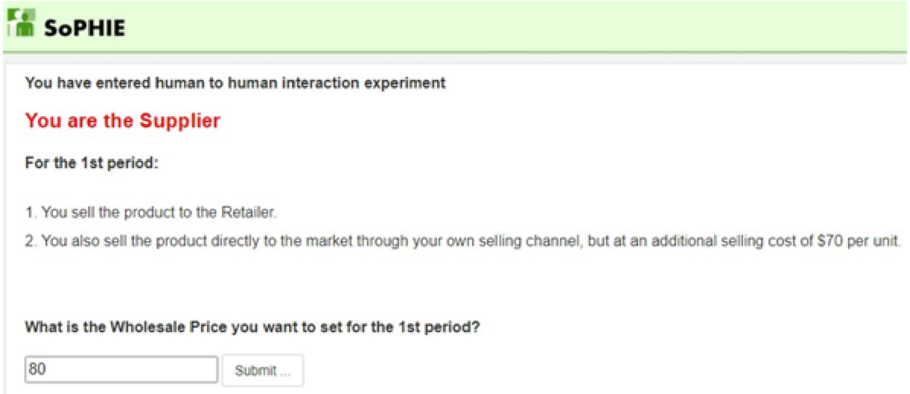
Market Price

Market Price depends on the sum of both the Supplier and the Retailer Selling Quantity to the customers.

Market Price = 150 - 0.5*(Supplier's direct selling quantity + Retailer's selling quantity)

Example 1:
if Supplier Direct Selling Quantity = 50, Retailer Selling Quantity = 60, the Market Price = 95

Example 2:
if Supplier Direct Selling Quantity = 100, Retailer Selling Quantity = 120, the Market Price = 40
Market Price changes by the sum of both the Supplier and the Retailer Selling Quantity to the market.
Therefore, in the beginning of the 1st period, both the Supplier and the Retailer should plan for the Selling, Ordering, and Inventory Quantity for the entire experiment.



SoPHIE

You have entered human to human interaction experiment

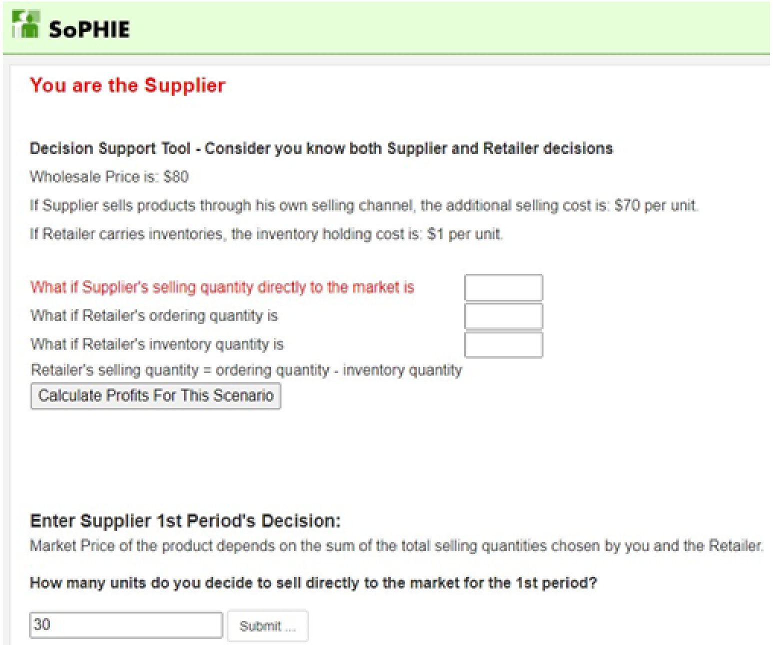
You are the Supplier

For the 1st period:

1. You sell the product to the Retailer.
2. You also sell the product directly to the market through your own selling channel, but at an additional selling cost of $70 per unit.

What is the Wholesale Price you want to set for the 1st period?

80 Submit ...



SoPHIE

You are the Supplier

Decision Support Tool - Consider you know both Supplier and Retailer decisions

Wholesale Price is: $80

If Supplier sells products through his own selling channel, the additional selling cost is: $70 per unit.

If Retailer carries inventories, the inventory holding cost is: $1 per unit.

What if Supplier's selling quantity directly to the market is

What if Retailer's ordering quantity is

What if Retailer's inventory quantity is

Retailer's selling quantity = ordering quantity - inventory quantity

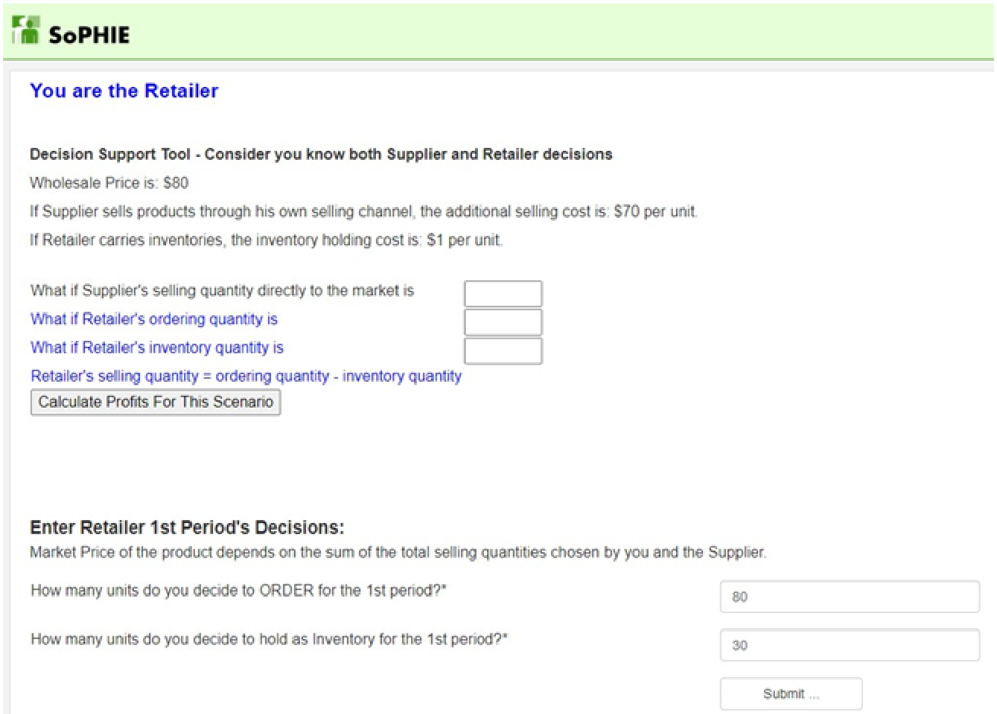
Calculate Profits For This Scenario

Enter Supplier 1st Period's Decision:

Market Price of the product depends on the sum of the total selling quantities chosen by you and the Retailer.

How many units do you decide to sell directly to the market for the 1st period?

30 Submit ...



SoPHIE

You are the Retailer

Decision Support Tool - Consider you know both Supplier and Retailer decisions

Wholesale Price is: $80

If Supplier sells products through his own selling channel, the additional selling cost is: $70 per unit.

If Retailer carries inventories, the inventory holding cost is: $1 per unit.

What if Supplier's selling quantity directly to the market is

What if Retailer's ordering quantity is

What if Retailer's inventory quantity is

Retailer's selling quantity = ordering quantity - inventory quantity

Calculate Profits For This Scenario

Enter Retailer 1st Period's Decisions:

Market Price of the product depends on the sum of the total selling quantities chosen by you and the Supplier.

How many units do you decide to ORDER for the 1st period?* 80

How many units do you decide to hold as Inventory for the 1st period?* 30

Submit ...

SoPHIE

You are the Supplier

For the 2nd period:

Wholesale Price for the 1st period was: $80

If you sell through your own selling channel, the additional selling cost is: $70 per unit

Retailer's inventory quantity is: 30

What is the Wholesale Price you want to set for the 2nd period?

60 Submit ...

SoPHIE

You are the Supplier

Decision Support Tool - Consider you know both Supplier and Retailer decisions

Wholesale Price is: $60

If Supplier sells products through his own selling channel, the additional selling cost is: $70 per unit

Retailer's inventory quantity is: 30

Retailer cannot carry any inventory for the 2nd period. All units Retailer ordered plus any inventory from the 1st period must be sold in the 2nd period.

What if Supplier's selling quantity directly to the market is

What if Retailer's ordering quantity is

Retailer's selling quantity = Inventory quantity + ordering quantity

Calculate Profits For This Scenario

Enter Supplier 2nd Period Decision:

Market Price of the product depends on the sum of the total selling quantities chosen by you and the Retailer.

How many units do you decide to sell directly to the market for the 2nd period?

40 Submit ...

SoPHIE

You are the Retailer

Decision Support Tool - Consider you know both Supplier and Retailer decisions

Wholesale Price is: $60

If Supplier sells products through his own selling channel, the additional selling cost is: $70 per unit

Retailer's inventory quantity is: 30

Retailer cannot carry any inventory for the 2nd period. All units Retailer ordered plus any inventory from the 1st period must be sold in the 2nd period.

What if Supplier's selling quantity directly to the market is

What if Retailer's ordering quantity is

Retailer's selling quantity = Inventory quantity + ordering quantity

Calculate Profits For This Scenario

Enter Retailer 2nd Period's Decision:

Market Price of the product depends on the sum of the total selling quantities chosen by you and the Supplier.

Retailer's Inventory quantity is: 30

How many units do you decide to ORDER for the 2nd period?* 50

Submit ...

Appendix A4: Additional Regression Analysis Results

Regression: Supplier and Retailer Selling Quantity over Wholesale price

	z_{s1} over w_1		z_{r1} over w_1	
	Intercept	w_1	Intercept	w_1
HLCL	50.5085***	0.2386*	58.6804***	-0.2838***
HHCL	47.2833***	0.3245***	62.7953***	-0.3113***
HLCH	47.9769***	0.1776*	49.0400***	-0.1540*
HHCH	24.3846***	0.5192***	65.7872***	-0.3260***
Best-Response	-	0.6667	-	-1.3333

***, **, * for the significance of <0.01, <0.05, <0.1

Appendix A5: Additional QRE Results

Model Estimation with Risk Aversion

	H_LC_L	H_HC_L	H_LC_H	H_HC_H
-Log likelihood	991.41	981.26	934.31	884.01
γ_{w2}: wholesale price bounded rationality	0.002331 (0.002)	0.000130 (0.000)	0.001200 (0.000)	0.001830 (0.001)
γ_{zs2}: supplier selling bounded rationality	0.000116 (0.000)	0.000170 (0.000)	0.001070 (0.004)	0.000891 (0.000)
γ_{zr}: retailer selling bounded rationality	0.000509 (0.000)	0.000905 (0.000)	0.001130 (0.000)	0.001543 (0.000)
β: risk aversion	0.012487 (1.000)	0.004710 (0.891)	0.000119 (0.485)	0.048563 (0.137)

Note: p-values are in parentheses

Model Estimation with Loss Aversion

	H_LC_L	H_HC_L	H_LC_H	H_HC_H
-Log likelihood	991.41	980.47	934.19	883.12
γ_{w2}: wholesale price bounded rationality	0.002821 (0.000)	0.000547 (0.009)	0.001351 (0.000)	0.000323 (0.008)
γ_{zs2}: supplier selling bounded rationality	0.000033 (0.002)	0.001275 (0.017)	0.001424 (0.000)	0.000933 (0.000)
γ_{zr}: retailer selling bounded rationality	0.000340 (0.000)	0.000894 (0.000)	0.000874 (0.002)	0.000875 (0.014)
β: loss aversion	1.004578 (0.337)	1.610210 (0.740)	1.771910 (0.694)	1.244386 (0.257)

Note: p-values are in parentheses

- Constant absolute risk aversion (CARA): $u_r = \frac{1-e^{-rE\pi_r}}{r}$, where r is the risk aversion parameter. We use the CARA formulation to capture the retailer's loss.
- Loss aversion: $u_r = \frac{E\pi_r, if \pi_r \geq 0}{\lambda E\pi_r, if \pi_r < 0}$, where λ is the loss aversion parameter.

- Belief: $(d - \alpha(z_{s2} + z_{r2}))(1 + \beta_{s/r})$, where β is the belief of period 2 market price.
- Fairness: $u_r = \pi_r - \theta \max(\pi_s - \pi_r, 0)$, where θ is the fairness concern.
- Akaike Information Criterion (AIC) Comparison

Akaike Information Criterion (AIC) Comparison

	$H_L C_L$	$H_H C_L$	$H_L C_H$	$H_H C_H$
Fairness	1976.08	1963.88	1855.42	1752.68
Risk Aversion	1990.82	1970.52	1876.62	1776.02
Loss Aversion	1990.82	1968.94	1876.38	1774.24
Belief	1895.62	1865.44	1816.88	1722.70

Note: Results are also consistent in BIC.

Appendix B

PROOF OF THE RESULTS IN CHAPTER 3

Appendix B1: Supplemental Proofs

Assumptions: $A_1 = 0;\ B_1 = B;\ A_2 = 0;\ B_2 = B;\ 0 \le h \le\ p;\ 0 \le c \le\ p$

A1. Expected Profits - Commit to Inventory Disposal:

$$s_1\ =\ (w_1\ -\ c)o_1$$

$$r_1\ =\ p(\int_{A_1}^{o_1} x_1 f(x_1)d_{x1} + \int_{o_1}^{B_1} o_1 f(x_1)d_{x1})\ -\ w_1 o_1$$

$$s_2\ =\ (w_2\ -\ c)o_{\ 2}$$

$$r_2\ =\ p(\int_{A_2}^{o_2} x_2 f(x_2)d_{x2} + \int_{o_2}^{B_2} o_2 f(x_2)d_{x2})\ -\ w_2 o_2$$

where f is the density function of the market demand.

Equilibrium:

$$o_2 = \frac{B(p-c)}{2p};\ w_2 = \frac{c+p}{2};\ o_1 = \frac{B(p-c)}{2p};\ w_1 = \frac{c+p}{2}$$

Expected Profits:

$$supplier_{disposal} = \frac{B(p-c)^2}{2p};\ retailer_{disposal} = \frac{B(p-c)^2}{4p};\ supply\ chain_{disposal}$$
$$= \frac{3B(p-c)^2}{4p}$$

A2. Expected Profits - Commit to Inventory Carryover:

$$s_1\ =\ (w_1\ -\ c)o_1$$

$$r_1\ =\ p\left(\int_{A_1}^{o_1} x_1 f(x_1)d_{x1} + \int_{o_1}^{B_1} o_1 f(x_1)d_{x1}\right) -\ w_1 o_1$$
$$- h\left(\int_{A_1}^{o_1} (o_1 - x_1)f(x_1)d_{x1} + \int_{o_1}^{B_1} 0 f(x_1)d_{x1}\right)$$

$$s_2\ =\ (w_2\ -\ c)o_2$$

$$r_2\ =\ p(\int_{A_2}^{o_2+i} x_2 f(x_2)d_{x2} + \int_{o_2+i}^{B_2} (o_2+i) f(x_2)d_{x2})\ -\ w_2 o_2$$

where inventory $i = \max\,(o_1 - d_1, 0)$.

Condition 1: when $\left(0 \le c \le \frac{p}{5} \& 0 \le h < p\right) || (\frac{p}{5} < c < p \& 0 \le h \le \frac{1}{4}(-5c + 5p)$

$w_1 = \frac{1}{98p}(-10c^2 + 12ch + 16h^2 + 62cp - 12hp + 46p^2 + x)$

$supplier_{inventory} = \frac{1}{111132p^2}B(-9261(c-p)^3 - 1323(c-p)^2(7c - 28h - 28p + y) + (28c - 28h - 28p + y)^3 + 54(-10c^2 + 16h^2 + 12c(h - 3p) - 12hp + 46p^2 + x)(7c - 28h - 7p + y))$

$retailer_{inventory} = \frac{1}{74088p^2}B(3206c^3 - 27776h^3 - 4529p^3 + 252px + 1346p^2y - 24xy + 32h^2(-1281p + 37y) + c^2(-21336h - 10941p + 338y) + 8h(-7959p^2 + 126x + 134py) - 4c(-10248h^2 - 3066p^2 + 63x + 421py + 4h(-5313p + 67y)))$

where $x = \sqrt{2}\sqrt{(5c + 4h - 5p)^2(2c^2 - 8ch + 8h^2 - 11cp + 8hp + 9p^2)}$

$y = \sqrt{169c^2 - 536ch + 592h^2 - 842cp + 536hp + 673p^2 - 12x}$

Condition 2: when $\boldsymbol{\frac{p}{5} < c < p \& \frac{1}{4}(-5c + 5p) < h < p}$

$w_1 = \frac{1}{98p}(-10c^2 + 12ch + 16h^2 + 62cp - 12hp + 46p^2 - x)$

$supplier_{inventory} = \frac{1}{111132p^2}B(-9261(c-p)^3 - 1323(c-p)^2(7c - 28h - 28p + z) + (28c - 28h - 28p + z)^3 - 54(10c^2 - 16h^2 - 12c(h - 3p) + 12hp - 46p^2 + x)(7c - 28h - 7p + z))$

$retailer_{inventory} = \frac{1}{74088p^2}B(3206c^3 - 27776h^3 - 4529p^3 - 252px + 1346p^2z + 24xz + 32h^2(-1281p + 37z) + c^2(-21336h - 10941p + 338z) - 8h(7959p^2 + 126x - 134pz) + 4c(10248h^2 + 3066p^2 + 63x - 421pz + 4h(5313p + 67z)))$

where $x = \sqrt{2}\sqrt{(5c + 4h - 5p)^2(2c^2 - 8ch + 8h^2 - 11cp + 8hp + 9p^2)}$

$z = \sqrt{169c^2 - 536ch + 592h^2 - 842cp + 536hp + 673p^2 + 12x}$

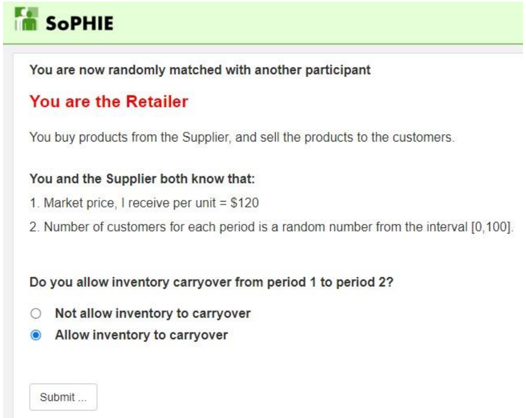
A3. Profit Comparisons:

when $retailer_{disposal} \geq retailer_{carryover}$:

Condition A1: When $(0 \leq c \leq \frac{941p}{384} - \frac{121}{128}\sqrt{\frac{19}{3}}\sqrt{p^2} \& 0 \leq h < p)||(\frac{941p}{384} - \frac{121}{128}\sqrt{\frac{19}{3}}\sqrt{p^2} < c \leq \frac{p}{5} \& Root[-576c^3 + 3399c^2p - 3022cp^2 + 199p^3 + (2560c^2 - 4800cp + 2240p^2)\#1 + (-3328c + 2304p)\#1^2 + 1024\#1^3\&, 1] \leq h < p)||(\frac{p}{5} < c < \frac{3089p}{3136} - \frac{23\sqrt{3473}\sqrt{p^2}}{3136} \& Root[-576c^3 + 3399c^2p - 3022cp^2 + 199p^3 + (2560c^2 - 4800cp + 2240p^2)\#1 + (-3328c + 2304p)\#1^2 + 1024\#1^3\&, 1] \leq h \leq \frac{1}{4}(-5c + 5p))||(c = (3089p)/3136 - \frac{23\sqrt{3473}\sqrt{p^2}}{3136} \& h = \frac{1}{4}(-5c + 5p))$

Condition A2: When $(\frac{p}{5} < c \leq \frac{3089p}{3136} - \frac{23\sqrt{3473}\sqrt{p^2}}{3136} \& \frac{1}{4}(-5c + 5p) < h < p)||(\frac{3089p}{3136} - \frac{23\sqrt{3473}\sqrt{p^2}}{3136} < c < p \& Root[-576c^3 + 3399c^2p - 3022cp^2 + 199p^3 + (2560c^2 - 4800cp + 2240p^2)\#1 + (-3328c + 2304p)\#1^2 + 1024\#1^3\&, 1] \leq h < p)$

Appendix B2: Experiment Screenshot



SoPHIE

You are now randomly matched with another participant

You are the Retailer

You buy products from the Supplier, and sell the products to the customers.

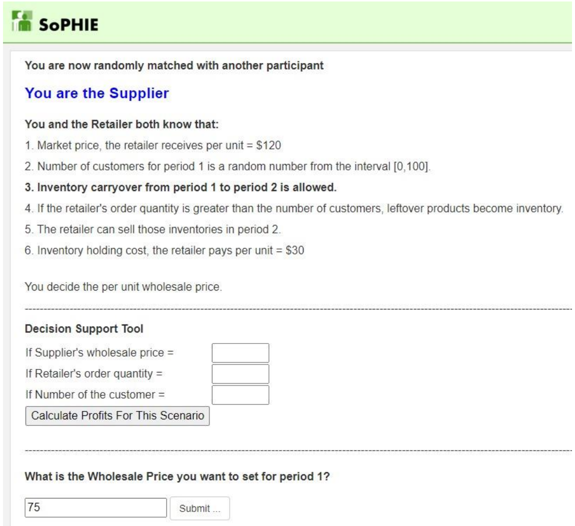
You and the Supplier both know that:

1. Market price, I receive per unit = $120
2. Number of customers for each period is a random number from the interval [0,100].

Do you allow inventory carryover from period 1 to period 2?

- Not allow inventory to carryover
- Allow inventory to carryover

Submit ...



SoPHIE

You are now randomly matched with another participant

You are the Supplier

You and the Retailer both know that:

1. Market price, the retailer receives per unit = $120
2. Number of customers for period 1 is a random number from the interval [0,100].
3. Inventory carryover from period 1 to period 2 is allowed.
4. If the retailer's order quantity is greater than the number of customers, leftover products become inventory.
5. The retailer can sell those inventories in period 2.
6. Inventory holding cost, the retailer pays per unit = $30

You decide the per unit wholesale price.

Decision Support Tool

If Supplier's wholesale price =

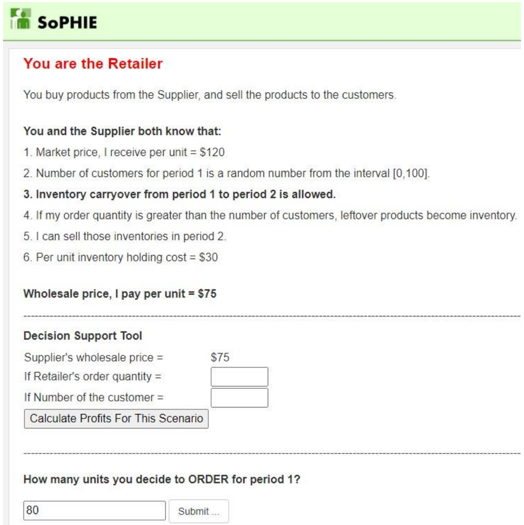
If Retailer's order quantity =

If Number of the customer =

Calculate Profits For This Scenario

What is the Wholesale Price you want to set for period 1?

75 Submit ...



SoPHIE

You are the Retailer

You buy products from the Supplier, and sell the products to the customers.

You and the Supplier both know that:

1. Market price, I receive per unit = $120
2. Number of customers for period 1 is a random number from the interval [0,100].
3. Inventory carryover from period 1 to period 2 is allowed.
4. If my order quantity is greater than the number of customers, leftover products become inventory.
5. I can sell those inventories in period 2.
6. Per unit inventory holding cost = $30

Wholesale price, I pay per unit = $75

Decision Support Tool

Supplier's wholesale price = $75

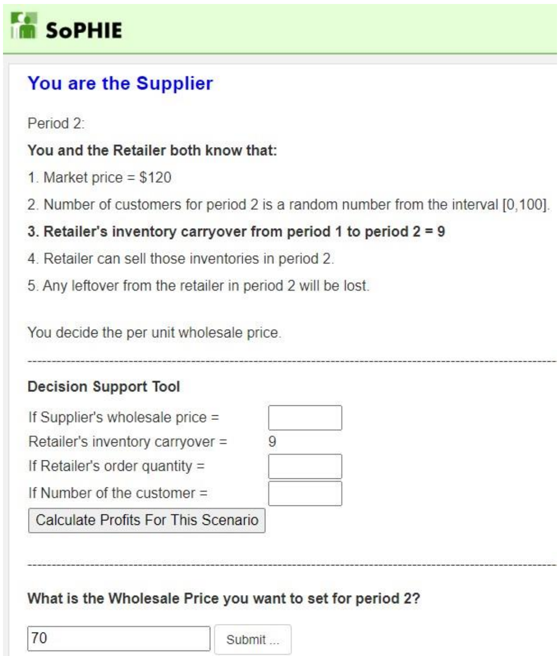
If Retailer's order quantity =

If Number of the customer =

Calculate Profits For This Scenario

How many units you decide to ORDER for period 1?

80 Submit ...



SoPHIE

You are the Supplier

Period 2:

You and the Retailer both know that:

1. Market price = $120
2. Number of customers for period 2 is a random number from the interval [0,100].
3. Retailer's inventory carryover from period 1 to period 2 = 9
4. Retailer can sell those inventories in period 2.
5. Any leftover from the retailer in period 2 will be lost.

You decide the per unit wholesale price.

Decision Support Tool

If Supplier's wholesale price =

Retailer's inventory carryover = 9

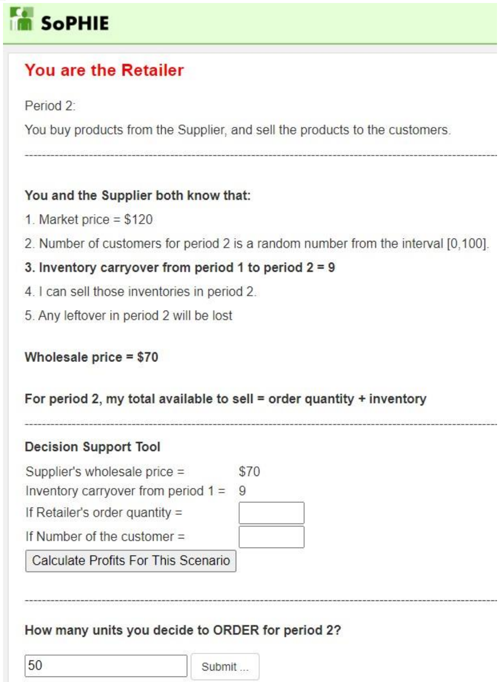
If Retailer's order quantity =

If Number of the customer =

Calculate Profits For This Scenario

What is the Wholesale Price you want to set for period 2?

70 Submit ...



SoPHIE

You are the Retailer

Period 2:

You buy products from the Supplier, and sell the products to the customers.

You and the Supplier both know that:

1. Market price = $120
2. Number of customers for period 2 is a random number from the interval [0,100].
3. Inventory carryover from period 1 to period 2 = 9
4. I can sell those inventories in period 2.
5. Any leftover in period 2 will be lost

Wholesale price = $70

For period 2, my total available to sell = order quantity + inventory

Decision Support Tool

Supplier's wholesale price = $70

Inventory carryover from period 1 = 9

If Retailer's order quantity =

If Number of the customer =

Calculate Profits For This Scenario

How many units you decide to ORDER for period 2?

50 Submit ...

Appendix C

PROOF OF THE RESULTS IN CHAPTER 4

Appendix C1: Supplemental Proofs

A. Constant Demand: $\mathrm{A1}=0, \mathrm{B1}=1, \mathrm{A2}=0, \mathrm{B2}=1$

A1. Expected Profit - Inventory Disposal:

$$\mathrm{s1}=\mathrm{w1o1}$$

$$\mathrm{r1}=p(\mathrm{Integrate}[\mathrm{d1}/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{A1},\mathrm{o1}\}]+\mathrm{Integrate}[\mathrm{o1}/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{o1},\mathrm{B1}\}]) \\ -\mathrm{w1o1}$$

$$\mathrm{s2}=\mathrm{w2o2}(1-r)$$

$$\mathrm{r2}=(p(\mathrm{Integrate}[\mathrm{d2}/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},\mathrm{A2},\mathrm{o2}\}]+\mathrm{Integrate}[\mathrm{o2}/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},\mathrm{o2},\mathrm{B2}\}]) \\ -\mathrm{w2o2})(1-r)$$

where A1, B1, A2, B2 are the market demand range; r is the production disruption risk.

Best-response: $\mathrm{o2}=\frac{p-\mathrm{w2}}{p}$, $\mathrm{w2}=\frac{p}{2}$, $\mathrm{o1}=\frac{p-\mathrm{w1}}{p}$, $\mathrm{w1}=\frac{p}{2}$

Equilibrium: $\mathrm{o2}=\frac{1}{2}$, $\mathrm{w2}=\frac{p}{2}$, $\mathrm{o1}=\frac{1}{2}$, $\mathrm{w1}=\frac{p}{2}$

Expected Profits:

$$\mathrm{retailer}_{\mathrm{disposal}}=\frac{1}{8}(2-r)p$$

$$\mathrm{supplier}_{\mathrm{disposal}}=\frac{1}{4}(2-r)p$$

A2. Expected Profit - Inventory Carryover:

$$\mathrm{s1}=\mathrm{w1o1}$$

$$\mathrm{r1}=p(\mathrm{Integrate}[\mathrm{d1}/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{A1},\mathrm{o1}\}]+\mathrm{Integrate}[\mathrm{o1}/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{o1},\mathrm{B1}\}]) \\ -\mathrm{w1o1}-h(\mathrm{Integrate}[(\mathrm{o1}-\mathrm{d1})/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{A1},\mathrm{o1}\}] \\ +\mathrm{Integrate}[0/(\mathrm{B1}-\mathrm{A1}),\{\mathrm{d1},\mathrm{o1},\mathrm{B1}\}])$$

$$\mathrm{s2}=\mathrm{w2o2}(1-r)$$

$$\mathrm{r2}=(p(\mathrm{Integrate}[\mathrm{d2}/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},\mathrm{A2},(\mathrm{o2}+n)\}] \\ +\mathrm{Integrate}[(\mathrm{o2}+n)/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},(\mathrm{o2}+n),\mathrm{B2}\}])-\mathrm{w2o2})(1-r) \\ +(p(\mathrm{Integrate}[\mathrm{d2}/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},\mathrm{A2},n\}] \\ +\mathrm{Integrate}[n/(\mathrm{B2}-\mathrm{A2}),\{\mathrm{d2},n,\mathrm{B2}\}]))r$$

where A1, B1, A2, B2 are the market demand range; r is the production disruption risk; n is the inventory level.

Best-response: $o2 = \frac{p-np-w2}{p}$, $w2 = -\frac{1}{2}(-1+n)p$

$$o1 = \frac{-4h - p + pr + 4\sqrt{(-h - \frac{p}{4} + \frac{pr}{4})^2 - 4(-\frac{3p}{8} - \frac{pr}{8})(p - w1)}}{3p + pr}$$

$$n = \text{Integrate}[(o1 - d1)/(B1 - A1), \{d1, A1, o1\}] + \text{Integrate}[0/(B1 - A1), \{d1, o1, B1\}]$$

$w1 \mid r \geq 46.89\%$

$$= \frac{1}{2(98p + 140pr + 50pr^2)}(32h^2 - 24hp + 92p^2 + 96h^2r + 80hpr + 236p^2r - 56hpr^2 + 52p^2r^2 + 4p^2r^3 - \surd((-32h^2 + 24hp - 92p^2 - 96h^2r - 80hpr - 236p^2r + 56hpr^2 - 52p^2r^2 - 4p^2r^3)^2 - 4(98p + 140pr + 50pr^2)(16h^2p - 8hp^2 + 17p^3 + 48h^2pr + 48hp^2r + 97p^3r - 40hp^2r^2 + 11p^3r^2 + 3p^3r^3)))$$

$w1 \mid r < 46.89\%$

$$= \frac{1}{2(98p + 140pr + 50pr^2)}(32h^2 - 24hp + 92p^2 + 96h^2r + 80hpr + 236p^2r - 56hpr^2 + 52p^2r^2 + 4p^2r^3 + \surd((-32h^2 + 24hp - 92p^2 - 96h^2r - 80hpr - 236p^2r + 56hpr^2 - 52p^2r^2 - 4p^2r^3)^2 - 4(98p + 140pr + 50pr^2)(16h^2p - 8hp^2 + 17p^3 + 48h^2pr + 48hp^2r + 97p^3r - 40hp^2r^2 + 11p^3r^2 + 3p^3r^3)))$$

Expected Profits:

$\text{retailer}_{\text{carryover}} \mid r \geq 46.89\%$

$$= -\frac{1}{24p^2(3+r)^2(7+5r)^2}(3968h^3 + 5856h^2p + 9096hp^2 + 647p^3 + 1280h^3r - 4512h^2pr + 3264hp^2r - 2059p^3r + 896h^3r^2 - 864h^2pr^2 + 4752hp^2r^2 + 326p^3r^2 - 480h^2pr^3 + 1152hp^2r^3 + 682p^3r^3 + 168hp^2r^4 + 355p^3r^4 + 49p^3r^5 + 144\sqrt{2}hx + 36\sqrt{2}px + 48\sqrt{2}hrx - 24\sqrt{2}prx - 12\sqrt{2}pr^2x - 1184h^2y - 1072hpy - 1346p^2y - 960h^2ry + 528hpry - 888p^2ry - 416h^2r^2y + 368hpr^2y - 620p^2r^2y + 176hpr^3y - 184p^2r^3y - 34p^2r^4y - 24\sqrt{2}xy - 8\sqrt{2}rxy)$$

$$\text{supplier}_{\text{carryover}} \mid \mathrm{r} \geq 46.89\%$$
$$= \frac{1}{12}(\frac{1}{3+r}3(-1+r)(-4h-4p+y)+\frac{1}{p^2(3+r)(7+5r)^2}6(16h^2(1+3r)-4hp(3-10r+7r^2)+2p^2(23+59r+13r^2+r^3)-\sqrt{2}x)(-4h-p+pr+y)-\frac{1}{p^2(3+r)^3}(-1+r)(p^3(3+r)^3+(-4h-4p+y)^3))$$

$$\text{retailer}_{\text{carryover}} \mid \mathrm{r} < 46.89\%$$
$$= -\frac{1}{24p^2(3+r)^2(7+5r)^2}(3968h^3+5856h^2p+9096hp^2+647p^3+1280h^3r-4512h^2pr+3264hp^2r-2059p^3r+896h^3r^2-864h^2pr^2+4752hp^2r^2+326p^3r^2-480h^2pr^3+1152hp^2r^3+682p^3r^3+168hp^2r^4+355p^3r^4+49p^3r^5-144\sqrt{2}hx-36\sqrt{2}px-48\sqrt{2}hrx+24\sqrt{2}prx+12\sqrt{2}pr^2x-1184h^2y-1072hpy-1346p^2y-960h^2ry+528hpry-888p^2ry-416h^2r^2y+368hpr^2y-620p^2r^2y+176hpr^3y-184p^2r^3y-34p^2r^4y+24\sqrt{2}xy+8\sqrt{2}rxy)$$

$$\text{supplier}_{\text{carryover}} \mid \mathrm{r} < 46.89\%$$
$$= \frac{1}{12}(\frac{1}{3+r}3(-1+r)(-4h-4p+y)+\frac{1}{p^2(3+r)(7+5r)^2}6(16h^2(1+3r)-4hp(3-10r+7r^2)+2p^2(23+59r+13r^2+r^3)+\sqrt{2}x)(-4h-p+pr+y)-\frac{1}{p^2(3+r)^3}(-1+r)(p^3(3+r)^3+(-4h-4p+y)^3))$$

where $x = \sqrt{(-4h(1+3r)+p(5-6r+r^2))^2(8h^2-8hp(-1+r)+p^2(9+r+2r^2))}$

$$y = \sqrt{}(\frac{1}{(7+5r)^2}(-8hp(-1+r)(67+r(34+11r))+16h^2(37+r(30+13r))+4\sqrt{2}(3+r)x+p^2(673+r(444+r(310+r(92+17r))))))$$

A3. Profit Comparisons:

Assumption: $0 \leq h \leq 1/4p$

If $0 \leq r \leq 51.03\%$: $\text{retailer}_{\text{carryover}} \leq \text{retailer}_{\text{disposal}}$; $\text{supplier}_{\text{disposal}} \leq \text{supplier}_{\text{carryover}}$

If $51.03\% < r \leq 1$: $\text{retailer}_{\text{disposal}} \leq \text{retailer}_{\text{carryover}}$; $\text{supplier}_{\text{disposal}} \leq \text{supplier}_{\text{carryover}}$

B. Decreasing Demand: $\mathrm{A1} = 0, \mathrm{B1} = 1, \mathrm{A2} = 0, \mathrm{B2} = 1/2$

B1. Expected Profit - Inventory Disposal:

$$\text{retailer}_{\text{disposal}} = \frac{1}{16} p(3-r)$$

$$\text{supplier}_{\text{disposal}} = \frac{1}{8} p(3-r)$$

B2. Expected Profit - Inventory Carryover:

$\text{retailer}_{carryover} \mid r \geq 46.89\%$

$$= \frac{1}{48p^2(3+r)^2(7+5r)^2}(-1984h^3 - 2928h^2p - 7572hp^2 - 418p^3 - 640h^3r + 2256h^2pr - 5808hp^2r + 1466p^3r - 448h^3r^2 + 432h^2pr^2 - 4152hp^2r^2 + 92p^3r^2 + 240h^2pr^3 - 816hp^2r^3 - 668p^3r^3 - 84hp^2r^4 - 410p^3r^4 - 62p^3r^5 - 144hx - 36px - 48hrx + 24prx + 12pr^2x + 592h^2y + 536hpy + 1177p^2y + 480h^2ry - 264hpry + 1140p^2ry + 208h^2r^2y - 184hpr^2y + 606p^2r^2y - 88hpr^3y + 132p^2r^3y + 17p^2r^4y + 24xy + 8rxy)$$

$\text{supplier}_{\text{carryover}} \mid r \geq 46.89\%$

$$= \frac{1}{48}\left(-\frac{1}{3+r}3(-1+r)(4h+7p+pr-y) + \frac{1}{p^2(3+r)(7+5r)^2}12(51p^2 + 107p^2r + 33p^2r^2 + p^2r^3 + 8h^2(1+3r) - 2hp(3-10r+7r^2) - x)(-4h-p+pr+y) - \frac{1}{p^2(3+r)^3}(-1+r)(p^3(3+r)^3 + (-4h-4p+y)^3)\right)$$

$\text{retailer}_{carryover} \mid r < 46.89\%$

$$= -\frac{1}{48p^2(3+r)^2(7+5r)^2}(1984h^3 + 2928h^2p + 7572hp^2 + 418p^3 + 640h^3r - 2256h^2pr + 5808hp^2r - 1466p^3r + 448h^3r^2 - 432h^2pr^2 + 4152hp^2r^2 - 92p^3r^2 - 240h^2pr^3 + 816hp^2r^3 + 668p^3r^3 + 84hp^2r^4 + 410p^3r^4 + 62p^3r^5 - 144hx - 36px - 48hrx + 24prx + 12pr^2x - 592h^2y - 536hpy - 1177p^2y - 480h^2ry + 264hpry - 1140p^2ry - 208h^2r^2y + 184hpr^2y - 606p^2r^2y + 88hpr^3y - 132p^2r^3y - 17p^2r^4y + 24xy + 8rxy)$$

$\text{supplier}_{\text{carryover}} \mid r < 46.89\%$

$$= \frac{1}{48}(-\frac{1}{3+r}3(-1+r)(4h+7p+pr-y) + \frac{1}{p^2(3+r)(7+5r)^2}12(51p^2+107p^2r+33p^2r^2+p^2r^3+8h^2(1+3r) - 2hp(3-10r+7r^2)+x)(-4h-p+pr+y) - \frac{1}{p^2(3+r)^3}(-1 + r)(p^3(3+r)^3+(-4h-4p+y)^3))$$

where $x = \sqrt{(-4h(1+3r)+p(5-6r+r^2))^2(4h^2-4hp(-1+r)+p^2(8+3r+r^2))}$

$$y = \sqrt{(\frac{1}{(7+5r)^2}(-8hp(-1+r)(67+r(34+11r))+16h^2(37+r(30+13r))-8(3 + r)x + p^2(1177+r(1140+r(606+r(132+17r))))))}$$

B3. Profit Comparisons:

Assumption: $0 \le h \le 1/4p$

If $0 \le r \le 7.9\%$: $\text{retailer}_{\text{carryover}} \le \text{retailer}_{\text{disposal}}$; $\text{supplier}_{\text{carryover}} \le \text{supplier}_{\text{disposal}}$

If $7.9\% \le r \le 1$: $\text{retailer}_{\text{disposal}} \le \text{retailer}_{\text{carryover}}$; $\text{supplier}_{\text{carryover}} \le \text{supplier}_{\text{disposal}}$

C. Increasing Demand: $\text{A1} = 0, \text{B1} = 1, \text{A2} = 0, \text{B2} = 3/2$

C1. Expected Profit - Inventory Disposal:

$\text{retailer}_{\text{disposal}} = \frac{1}{16}p(5-3r)$

$\text{supplier}_{\text{disposal}} = \frac{1}{8}p(5-3r)$

C2. Expected Profit - Inventory Carryover:

$\text{retailer}_{carryover} \mid r \ge 46.89\%$

$$= -\frac{1}{48p^2(3+r)^2(7+5r)^2}(17856h^3+26352h^2p+31860hp^2 + 2628p^3+5760h^3r-20304h^2pr+2160hp^2r-7956p^3r+4032h^3r^2 - 3888h^2pr^2+16056hp^2r^2+2232p^3r^2-2160h^2pr^3+4464hp^2r^3 + 2088p^3r^3+756hp^2r^4+900p^3r^4+108p^3r^5+432\sqrt{3}hx+108\sqrt{3}px + 144\sqrt{3}hrx-72\sqrt{3}prx-36\sqrt{3}pr^2x-1776\sqrt{3}h^2y-1608\sqrt{3}hpy - 1515\sqrt{3}p^2y-1440\sqrt{3}h^2ry+792\sqrt{3}hpry-636\sqrt{3}p^2ry - 624\sqrt{3}h^2r^2y+552\sqrt{3}hpr^2y-634\sqrt{3}p^2r^2y+264\sqrt{3}hpr^3y - 236\sqrt{3}p^2r^3y-51\sqrt{3}p^2r^4y-72xy-24rxy)$$

$$\begin{aligned}\text{Supplier}_{carryover} \mid r \geq 46.89\% &= \frac{1}{16(3+r)} 3(-1+r)(-12h-9p+pr+\sqrt{3}y) \\ &+ \frac{1}{4p^2(3+r)(7+5r)^2}(41p^2+129p^2r+19p^2r^2+3p^2r^3+24h^2(1 \\ &+3r)-6hp(3-10r+7r^2)-\sqrt{3}x)(-12h-3p+3pr+\sqrt{3}y) \\ &- \frac{1}{144p^2(3+r)^3}(-1+r)(27p^3(3+r)^3+(-12h-12p+\sqrt{3}y)^3)\end{aligned}$$

$$\begin{aligned}\text{retailer}_{carryover} \mid r < 46.89\% &= -\frac{1}{48p^2(3+r)^2(7+5r)^2}(17856h^3+26352h^2p+31860hp^2 \\ &+2628p^3+5760h^3r-20304h^2pr+2160hp^2r-7956p^3r+4032h^3r^2 \\ &-3888h^2pr^2+16056hp^2r^2+2232p^3r^2-2160h^2pr^3+4464hp^2r^3 \\ &+2088p^3r^3+756hp^2r^4+900p^3r^4+108p^3r^5-432\sqrt{3}hx-108\sqrt{3}px \\ &-144\sqrt{3}hrx+72\sqrt{3}prx+36\sqrt{3}pr^2x-1776\sqrt{3}h^2y-1608\sqrt{3}hpy \\ &-1515\sqrt{3}p^2y-1440\sqrt{3}h^2ry+792\sqrt{3}hpry-636\sqrt{3}p^2ry \\ &-624\sqrt{3}h^2r^2y+552\sqrt{3}hpr^2y-634\sqrt{3}p^2r^2y+264\sqrt{3}hpr^3y \\ &-236\sqrt{3}p^2r^3y-51\sqrt{3}p^2r^4y+72xy+24rxy)\end{aligned}$$

$$\begin{aligned}\text{Supplier}_{carryover} \mid r < 46.89\% &= \frac{1}{24}(\frac{1}{2(3+r)}9(-1+r)(-12h-9p+pr+\sqrt{3}y) \\ &+\frac{1}{p^2(3+r)(7+5r)^2}6(41p^2+129p^2r+19p^2r^2+3p^2r^3+24h^2(1 \\ &+3r)-6hp(3-10r+7r^2)+\sqrt{3}x)(-12h-3p+3pr+\sqrt{3}y)-p(-1 \\ &+r)(\frac{9}{2}+\frac{1}{6p^3(3+r)^3}(-12h-12p+\sqrt{3}y)^3))\end{aligned}$$

C3. Profit Comparisons:

Assumption: $0 \leq h \leq 1/4p$

If $0 \leq r \leq 34.75\%$: $\text{retailer}_{\text{carryover}} \leq \text{retailer}_{\text{disposal}}$; $\text{supplier}_{\text{disposal}} \leq \text{supplier}_{\text{carryover}}$

If $34.75\% < r \leq 1$: $\text{retailer}_{\text{disposal}} \leq \text{retailer}_{\text{carryover}}$; $\text{supplier}_{\text{disposal}} \leq \text{supplier}_{\text{carryover}}$

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