A BEHAVIORAL OPERATIONS MANAGEMENT STUDY OF MARKET POWER AND FUZZY RETURN

by

JINGJIE SU

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To my family

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Abstract

This dissertation studies the market power and the investment in the supply chain in the first two studies and the return policy of the retailer in the third study.

In the first study, we study how the dominant market power impacts the investment decision in the supply chain. We build a dual-channel supply chain model with two players, one is OEM and one is CM. Our research centers on the dominant market power, either OEM side or CM side, changing the investment decision of OEM. We solve the game theory model based on the setting and conduct the lab experiment to test the hypothesis.

In the second study, we extend the first study and explore how less-dominant market power affects the investment in the supply chain. We set up the same omni-channel supply chain model. There are two players in the model, retailer and supplier. We extend the investment decision to have more possible projects. Furthermore, we set the market power to be a percentage between 0 and 1. Using game theory, we solve the model theoretical prediction. We build a lab experiment to test the theory and set up behavior models to explain human bias.

In the third study, we focus on the return policy set by the retailer. We study a special type of return in this study, which is the return from consumers that is outside the standard policy, yet not totally unacceptable. We call this type of return as a fuzzy return. We build a model to simulate the retailer and consumer decisions during this fuzzy return process. We solve the conditions for the retailer to choose different types of fuzzy return.

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CHAPTER 1

Introduction

Supervising Professor: Kay-Yut Chen, Chair

In this dissertation, I employ game theory analysis to investigate and measure the importance of market power and consumer return in the perspective of behavioral operations management via three mini-studies.

In Chapter 2, we study the impacts of the dominant market power to the investment in a dual-channel supply chain setting. Classical reasons for an original equipment manufacturer (OEM) to invest in the production of a contract manufacturer (CM) include quality control, capacity constraints, or procurement costs. The last decades has seen active research in supply chain coordination focusing on the role of incentive contracts and supply chain integration to achieve the optimal efficiency. Does dominant market power influence the OEM investment in the production of CM? Conversely, can the investment decision of OEM purely due to the incentive effect? We prove that the OEM has the dominant market power, and the investment is lower than a specified threshold, he should always invest in the production of CM. Otherwise, he should not make the investment. We employ the combination of game theory and human-subject experiments, from a behavioral aspect, to investigate how the dominant market power impacts the OEM and the CM decisions in a dual channel setting. We find that both the OEM and the CM decisions were significantly deviated from theory predictions. Specifically, the OEM under invested when he has the market power and the investment cost is lower than the threshold, while over invested when the CM has the market power, or the investment cost is higher than the threshold. Also, both the dominant market power and the cost of the investment have a significant impact on the OEM and the CM decisions.

In Chapter 3, we further analyze the impacts of non-dominant market power to investment. Due to the advent of the online channel and ongoing digitalization, many firms have initiated multi-channel strategies, who have the market power becomes one of the important aspects in the supply chain. We employ a combination of game theory analyses, human-subject experiments, behavioral economics modeling, and numerical analyses to investigate the importance of the market power and changing in cost structures in decision making. We find that both the supplier and retailer decisions deviate from the theoretical predictions. However, statistical analyses cannot explain the experimental results given the strategic interactions of the supplier and retailer as well as noisy decision behaviors. Therefore, we develop a structural model incorporating bounded rational based on the quantal response equilibrium (QRE) framework to capture and measure the strategic responses of the supplier and the retailer while controlling the decision bias. Based on the behavioral model, we characterize how the supplier and the retailer decisions were affected by the bounded rationality through numerical analyses.

In Chapter 4, we build a model to design an optimal fuzzy return for the retailer. Due to the fast growth of internet technology and e-commerce, we have seen some significant increase in sales in e-commerce along with consumer returns. One of the most challenging problems sales managers face today is how to design an optimal return policy. We employ a combination of game theory and numerical analysis to investigate the importance of fuzzy return, which is one special type of consumer return. We theoretically prove that given the same expected value, the variance of the consumer value distribution has effects on the fuzzy return policy set by the retailer. We also show that the variance of signal distribution can impact the fuzzy return policy set by the retailer as well. Furthermore, we have identified a condition, which separates the fuzzy return policy into two strategies. The first strategy is to offer a short return, which is to accept none return during the fuzzy return stage. The second strategy for the retailer is to offer fuzzy return, which is to accept a proportion of return in the fuzzy return stage. With numerical analysis, we also observe a change of optimal return policy from short return to fuzzy return as the uncertainty of product increases. Furthermore, we also observe the degree of fuzzy return changes as the uncertainty of product increases. We conclude that the uncertainty of product and learning rate, as well as product price can impact what retailer should choose for the optimal return policy.

CHAPTER 2

How Dominant Market Power Impacts OEM Investments in the Supply Chain – Theory and Experiment

Jingjie Su, Kay-Yut Chen

College of Business, The University of Texas at Arlington

2.1 Introduction

Increasingly, contract manufacturers (CMs), whose original role is to be outsource partners for original equipment manufacturers (OEMs), compete with their OEM partners in the same markets (Arruñada & Vázquez, 2006). Well-known examples include Lenovo and Acer, who started as manufacturers for known brands like IBM and eventually became competitors in the same PC market. This supply chain structure resembles now well-studied omni/dual channel settings where a supplier (CM) sells to a retailer (OEM) but also sells directly to the customers. There are, however, two major differences.

First, the OEM/CM relationship is often beyond simple movement of products and the associated monetary transfer. Another important dimension of this relationship is investment, as one party (e.g. OEM) invests in the other (e.g. CM). Yu et al. (2006) has documented how OEMs have invested in the manufacturing capacity of CMs such as tools and equipment upgrades. In this paper, we focus on the issue of OEM investing in the CM, as it is more prevalent, although investments can go in the other direction. The most common result of this kind of investment is reduction of production costs for the entire supply chain (Sahay, 2003). Since CM is the manufacturer of the product, the investment could result in the decrease of production costs in the entire supply chain. The other reason for studying the OEM investing in the CM is that the scenario poses an interesting incentive problem. The investment benefits the whole supply chain, but it is a pure out-of-pocket cost for the OEM. The obvious answer is that the two parties contract on the investments and share the gains. Surprisingly, there is evidence that sometimes the OEM will invest without any formal agreements on subsequent supply chain contracts (e.g. wholesale price). Our study focuses on the phenomenon of this kind of "uncontracted" investment where the OEM relies on something else rather than formal contracts to recover the costs and may even share the gains.

One potential answer is "power." While there is literature exploring the definition and characteristics of power (Gaski, 1984), we take a more pragmatic approach and operationalize "power" as the ability to set the wholesale price. Hence, power, in this paper, is defined as a binary state. Either the OEM sets the wholesale price (i.e. OEM has power), or the CM does (i.e. CM has power). This setting is, in spirit, similar to Cui et al. (2016) although their setting is completely different from ours. We argue that when the OEM has power, it can extract the benefit of its investment from the CM better than when it does not have power. As a result, we argue that the OEM is more likely to invest when it has power. The main research question is whether this reasoning is correct. There are, of course, other possible explanations, such as reciprocity and other social interactions. The main goal of this paper is to investigate the role of power in uncontracted investment.

We employ a combination of game theory and human-subject experiments for this study.

Game theoretical analysis reveals that, indeed, in equilibrium, the OEM should invest only if he has power and the investment cost is below the threshold. However, it is well known that game theory does not always capture realistic human decision-making behaviors. Field studies will involve too many confounding factors, and in this case, pose the additional challenge of finding ways to measure power, and infer causality. Thus, lab-based human subject experimentation is the most promising approach. This is, indeed, in line with the current trend of behavioral operations management studies (please see Donohue et al. (2018) for a review of this literature). Laboratory experiments show that the OEM sometimes invests when it should not, but under-invests when it should. Interestingly, investments do not increase the OEM profit although they do increase total supply chain profits. We also find that the OEM is more sensitive to market power than investment costs.

The paper is structured as follows. In Section 2.2, we summarize the related theoretical and empirical literature in dual channel supply chain, integration and investment, supply chain market power, experiments in behavioral operations management. Section 2.3 provides the details of our model setting and game theory predictions. Section 2.4 describes our experimental design and hypotheses. Section 2.5 includes the experimental results and observation findings. Based on the findings we show, we propose the managerial insight of this article in section 2.6. We conclude the paper with limitations of this work and suggestions for future extensions in Section 2.7.

2.2 Literature Review

Four areas of research, either theoretical or empirical, are related to this study, the relationship of OEM and CM, the investment between two parties, the market power, and the experiments in the behavioral operations management.

There is a growing interest in the dual channel supply chain. Hilmola et al. (2005) document industry dual channel relationship examples. One practical example is that BenQ is not only the contract manufacturing company for big name companies, like Motorola and Nokia, but also offers its own product to the market. In Hilmola et al. (2005) review paper, they summarize prior multi-channel relationship literature and predict that companies will continue to adapt the multi-channel strategy in the future. Niu et al. (2015) study the pricing game in a dual channel setting of the OEM and the ODM. They conclude that the OEM and the ODM partnership is steady according to the equilibrium and this partnership weakens the competition between them. Wang et al. (2013) study three different types of competition between OEM and CM including simultaneous Cournot and either OEM or CM as the Stackelberg leader. Their model illustrates that in all three models, the OEM is better off when having the CM as the competitive partner. We differentiate our paper from the prior literature by incorporating an issue of unbounded investment contract into a complete information dual channel setting.

The second part of the literature focuses on supply chain integration and investment. According to The Mechanisms of Governance (Williamson, 1996), the author presents a theory that no firms should make any investments without solid monetary return contracts attached to this investment. This theory derives the basic condition of an investment behavior. However, in real world business, we observe some opposite investment behaviors. Kang et al. (2009) investigate how and why many firms would make unilateral investments to other firms without a bounded contract. They find that firms will make an unbounded investment if the investment yields potential strategic economical value. Another empirical study by Li and Lin (2006) find the evidence that the OEM will make the investment to the CM to maintain a sustainable relationship. In this paper, we induce the investment by adding competition and market power and provide the theoretical predictions for the OEM and the CM interactions.

Market Power, defined as a firm relative ability of a firm to control the price of a good or service in the marketplace by manipulating the level of supply, demand, or both (Frank, 2008), is well studied in marketing research. In this paper, we take a more pragmatic approach and operationalize "power" as the ability to set the wholesale price. Hence, we define power as a binary state and focus our discussion of power in the supply chain setting. Chen et al. (2012) analyze a model of the procurement decision made by the OEM depending on its bargaining power on wholesale price. They conclude that the procurement of OEM should be a threshold strategy and also depends on the power. In our paper, we combine power with investment and find a new way of inducing investment.

Prior behavioral operations management literature has shown that human decisions will deviate from theoretical predictions (Donohue et al., 2018). We conduct a series of controlled laboratory human-subjects experiments to investigate how and why the market power impacts the investment decisions.

As far as we know all previous papers are either empirical or analytical work. Our paper is the first paper to combine all the elements, including uncontracted investment, dual channel, power and human-subject experiments.

2.3 Model Setup and Theoretical Predictions

We consider a model with two players. The first player is the original equipment manufacturer (OEM), referred to as "he", buys the product from the CM at a wholesale price (w) and sells it to the market at a market price (P). The second player is the contract manufacturer (CM), referred to as "she", who can not only sell the product to the OEM but also sell to the market directly via her private channel at the same market price (P). The market price (P) is a linear downward slope function that depends on the total selling quantity of the OEM (Q_o) and the CM (Q_c) to the market.

Following the design philosophy of parsimony, we use the simplest model to explain the impact of the market power. We do not consider the excess inventory in the model. Hence, the selling quantity of OEM to market (Q_o) equals the ordering quantity from the CM. The profit function of the OEM is given in equation (2.1).

$$\pi_{OEM} = (P - w)Q_o \tag{2.1}$$

We assume the CM has an unlimited capacity that can fulfill all orders, and for every unit she produces, she pays a production cost (c). When the CM sells directly to the market, she receives the market price (P), but also pays an extra per unit market cost (c_m). The profit function of the CM is given in equation (2.2).

$$\pi_{CM} = (P - c - c_m)Q_c + (w - c)Q_o \tag{2.2}$$

The market price (P) function, which depends on the total selling quantity of the OEM and the CM to the market (Q_o and Q_c), is given in equation (2.3).

$$P = a - b(Q_o + Q_c) \tag{2.3}$$

where a is the maximum market demand, and b is the sensitivity of the price.

2.3.1 Theoretical Predictions - OEM has the market power

We first consider the situation that the OEM has the market power, which means the OEM sets the wholesale price. Based on Nash equilibrium (Nash, 1951), we can calculate the OEM optimal wholesale price (w^*), which is equal to the CM production cost (c). Please refer to Appendix A for the detailed solutions. The optimal profit of OEM is given in the equation (2.4).

$$\pi^*_{OEM} = \frac{1}{9b}(a - c + c_m)^2 \tag{2.4}$$

If the OEM decided to make an investment in the production of CM with an investment cost (I), the investment is going to lower the production cost of CM, from c to c_I, where $c > c_I$. Let P_I, w_I and Q_{oI} represent the market price, the wholesale price and the selling quantity of OEM when invested. The profit function of OEM is given by:

$$\pi_{OEMI} = (P_I - w_I)Q_{oI} - I \tag{2.5}$$

Let Q_{cI} be the quantity of the CM sells to the market. The profit function of the CM, assume the OEM invests, is given by:

$$\pi_{CMI} = (P_I - c_I - c_m)Q_{cI} + (w_I - c_I)Q_{oI} \tag{2.6}$$

The market price (P_I), assume the OEM invested, is given by:

$$P_I = a - b(Q_{oI} + Q_{cI}) \tag{2.7}$$

Hence, the optimal wholesale price that the OEM should set would be $w_I^* = c_I$, and the optimal profit of the OEM is given by:

$$\pi^*_{OEMI} = \frac{1}{9b}(a - c_I + c_m)^2 - I \tag{2.8}$$

This indicates that the condition under which the OEM would decide to invest in the production of CM only when $\pi^*_{OEMI} > \pi^*_{OEM}$. In order to satisfy this condition, the investment cost (I) must be less than a threshold, showing in equation (2.9).

$$I < \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I)) \tag{2.9}$$

This result shows that when the OEM has the market power to set the wholesale price, if the investment cost is less than the threshold in equation (2.9), the OEM should make the investment, based on Nash equilibrium (Nash, 1951). Conversely, If the investment cost is higher than the threshold, the OEM should not make the investment in the production of CM.

2.3.2 Theoretical Predictions - CM has the market power

Next, we consider the situation when the CM has the market power and is able to set the wholesale price. If the OEM decides not to invest in the production of CM, the profit functions of the OEM and the CM are the same as in equation (2.1) and (2.2). In this case, based on Nash equilibrium (Nash, 1951), the optimal wholesale price set by the CM is given in equation 2.10. Please refer to Appendix A for proofs.

$$w^* = \frac{5a + 5c - c_m}{10} \tag{2.10}$$

The optimal profit function of OEM is given by:

$$\pi^*_{OEM} = \frac{(4c_m^2)}{25b} \tag{2.11}$$

Conversely, if the OEM decides to invest in the production of CM, the profit functions of the OEM and the CM are the same as equation (2.5) and (2.6). Hence, the optimal profit function of the OEM is as shown in equation (2.12).

$$\pi^*_{OEMI} = \frac{(4c_m^2)}{25b} - I \tag{2.12}$$

Because of $\pi^*_{OEMI} < \pi^*_{OEM}$, hence, when the CM has the market power, regardless of investment cost, the OEM should never invest in the production of CM.

To summarize the theoretical results, based on Nash equilibrium (Nash, 1951), we solved the investment decision of OEM as a threshold strategy. That is, when the OEM has the market power to set the wholesale price and the investment cost is lower than the threshold (I^*), the OEM should always invest in the production of CM. If the investment cost is higher than the threshold (I^*), the OEM should not make the investment. On the other hand, when the CM has the market power to set the wholesale price, the OEM should never make the investment to reduce the production cost of CM.

$$I^* = \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I)) \tag{2.13}$$

Given the complexity of the strategic interactions in a dual channel Cournot quantity competition setting, and the multiple incentives and decisions in play, the goal of the paper is to conduct a human-subjects experiment to investigate the following two research questions.

1. When the OEM has the option to invest that can helps to reduce the production cost of CM, will his investment decision be affected by the changing of the investment cost?

2. Given the possible strategic interactions and noisy decision-making behaviors, will the market power, defined as who set the wholesale price, impact the investment decision of OEM?

2.4 Research Hypotheses and Experimental Design

Prior behavioral operations management literature has shown that human decisions will deviate from theoretical predictions (Donohue et al., 2018). Hence, we conduct a series of human-subject experiments to investigate the aforementioned research questions. To help clarify intent of the experimental design and calibration, we adapt the analytical results into testable hypotheses.

The first hypothesis is motivated by the theoretical result that the OEM should only make the investment when the OEM has the market power, and the investment cost is below the threshold.

HYPOTHESIS 1a. In the OEM-Low treatment, the OEM always makes the investment to reduce the CM's production cost.

HYPOTHESIS 1b. In OEM-High, CM-Low or CM-High treatment, the OEM does not make the investment.

HYPOTHESIS 1c. Compared with other treatments, the percentage of investment is the highest in the OEM-Low treatment.

The second hypothesis is related to the dynamic changing of the investment decision. Due to the Nash Equilibrium, there is no change of parameter.

HYPOTHESIS 2. There is no significant change of investment when period increases in all treatments.

The third set of hypotheses is related to the market power and changing of investment cost.

HYPOTHESIS 3a. Market power has a positive impact on the investment decision.

HYPOTHESIS 3b. The investment cost has a positive impact on the investment decision.

The last hypothesis for investment is in the perspective of the entire supply chain. Theory predicts that investment is an equilibrium if the supply chain is centralized (please refer to Appendix A).

HYPOTHESIS 4a. Total supply chain profit is the highest with the OEM investment, compared with other treatments.

HYPOTHESIS 4b. Total supply chain efficiency is the highest with the OEM investment, compared with other treatments.

Hypothesis 5 is related to the predicted wholesale price.

HYPOTHESIS 5. The wholesale price of the OEM and the CM will not deviate from the predictions.

The design of the experiments focuses on two key variables, the market power and the investment cost. We use a standard 22 between-subjects full factorial design for a total of four treatments. On the market power dimension, there are two scenarios. First scenario is the OEM has the market power to set the wholesale price, and the second scenario is the CM has the power to set up the wholesale price. On the investment cost dimension, it also has two scenarios. First scenario is that the investment cost is less than the threshold, refer to equation (2.13), and the second scenario is that the investment cost is higher than the threshold. In each treatment, we have about 24 subjects. Table 2.1 summarizes the experimental design and number of participants.

We use the game theoretic analysis as guidance to pick one parametric setting where the incentives are representative and deemed close to the real environment. Table 2.2 summarizes our parameter choices. Note that the investment cost of OEM/CM-Low and OEM/CM-High

Table 2.1: Experiment Design and Number of Participants

	When OEM has power	When CM has power
$I < I^*$	OEM-Low(24)	CM-Low(24)
$I > I^*$	OEM-High(24)	CM-High(26)

treatments are calibrated in the way that one is lower than the threshold and the other is higher than the threshold.

Table 2.2: Parameter Calibration

	OEM-Low	OEM-High	CM-Low	CM-High
Investment cost(I)	380	580	380	580
I^*	483.33	483.33	–	–
Production cost before investment (c)	40	40	40	40
Production cost before investment (c_I)	25	25	25	25
Extra market cost (c_m)	5	5	5	5

The game sequences are described as follows. In the first stage, the OEM observes who has the market power and decides whether to invest in the production of CM. In the second stage, after observing the investment decision from OEM, either OEM or CM, whoever has the market power, decides the wholesale price. In the third stage, both the OEM and the CM, after observing the investment and wholesale price decisions, decide the selling quantity to the market. The computer automatically calculates the profits for the OEM and the CM. All basic information, including the investment cost, production cost before and after investment are always shown in the Z-tree (Fischbacher, 2007) program screen (please refer to Appendix C for experiment screenshots).

In each treatment, about 24 subjects are randomly assigned to play a role as either the

OEM or the CM. Subjects are randomly paired in each round while keeping the same role, to form a group with one OEM and one CM for a total of 30 rounds.

We followed standard economic experimental procedures and used no deception. A total of 98 participants volunteered to participate and receive monetary compensation according to their performance. All participants are recruited from undergraduate students in the business school of a public university in the Southern USA. Each experiment session lasts about 90 minutes and it is conducted in the behavior lab, located in that university, using the behavior experiment software, Z-tree (Fischbacher, 2007). In each experiment session, the participants were told they would be asked to make decisions in a premade computer program. The instruction of experiment procedure is explained orally and written to the participants before they start the program. After the introduction of instruction, the participants were also asked to complete a quiz to ensure they understand the task. The average payment for each participant is about $15 USD.

2.5 Experimental Results

Table 2.3: Summary Statistics of Experiment Result

	OEM-Low	OEM-High	CM-Low	CM-High
Investment Percentage	53.61%	41.67%	33.33%	36.41%
Wholesale price (w)	43	39	72	74
Quantity of OEM (Q_o)	43	39	72	74
Quantity of CM (Q_c)	51	40	43	48
Price (P)	55	58	66	61
Profit of OEM (π_{OEM})	-76	370	-256	-797
Profit of CM (π_{CM})	665	862	1506	1795
Profit of Supply Chain ($\pi_{OEM} + \pi_{CM}$)	589	1232	1250	999

2.5.1 OEM under invested when they should and over invested when they should not.

Based on the theoretical prediction, the OEM should always make the investment to reduce the production cost of CM if the OEM has the power to set the wholesale price and the investment cost is lower than the threshold. This prediction can also refer as the investment percentage should be 100% in OEM-Low treatment. In the actual OEM-Low treatment, 12 OEMs made a total of 360 rounds of investment decisions. They decided to invest in the production cost of CM 193 rounds, which represents an investment rate of 53.61%. Proportion test indicates that the OEM investment decision is significantly (p-value < 0.01) different from the theory prediction. Hence, Hypothesis 1a is rejected, and the OEMs were under invested in the OEM-Low treatment.

The theory also predicts the OEM should not invest neither if the OEM has the market power, but the investment cost is higher than the threshold nor if the CM has the market power. This prediction can refer as the investment percentage should be 0% in OEM-High, CM-Low and CM-High treatment. Our experimental results show that in the OEM-High treatment, out of 360 investment decisions, the OEM chose to invest 150 times, which represents an investment rate of 41.67%. In the CM-Low treatment, out of 360 decisions, the OEM chose to invest 120 times, which represents an investment rate of 33.33%. Similar to the CM-High treatment, out of 390 decisions, the OEM chose to invest 142 times, which represents an investment rate of 36.41%. In all three treatments, the proportion test indicates that the OEM investment decision is significantly (p-value < 0.01) different from the theory prediction. Hence, Hypothesis 1b is rejected, and the OEMs were over invested in the OEM-High, CM-Low and CM-High treatments.

Since the theory predicts there is a 100% investment rate in the OEM-Low treatment and 0% investment rate in the other three treatments, this prediction can also refer to the OEM-Low treatments having a higher investment rate compared with the other three treatments. The one-sided proportion test shows that the investment percentage in OEM-Low is significantly (p-value < 0.01) higher than other three treatments. Hence, Hypothesis 1c is supported, when OEM has the market power and the investment cost is low, the investment rate is the highest.

Experimental results show that the market power and the low investment cost may induce a higher investment rate for the OEM. However, there is an under-investment pattern in the OEM-Low treatments and consistently over-investment pattern in OEM-High, CM-Low and CM-High treatments.

2.5.2 Dynamic impacts the OEM investment decision.

From Section 2.5.1, we observe clear evidence of under-investment in the OEM-Low treatment and over-investment in other three treatments. Because each OEM makes 30 rounds of investment decisions, we investigate whether dynamic impacts the investment decision from OEM. Although game theory assumes every round of the decision is independent across multiple periods, prior behavioral operation management literature has shown that individuals may be influenced by their prior decisions. We start by comparing the investment rate of four treatments in the first 5 rounds of decisions with the last 5 rounds of decisions. Table 2.4 displays the average investment rate and the p-values from the one-sided proportion test compared with 50%.

Table 2.4: Investment Percentage and Proportion Test Result

	OEM-Low	OEM-High	CM-Low	CM-High
Periods 1-5 (H_A: $p > 50\%$)	63%**	53%	50%	55%
Periods 26-30 (H_A: $p < 50\%$)	53%	35%**	26%**	24%**
$^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$				

In the first 5 rounds, we observe an investment rate that is significantly (proportion test, p-value < 0.01) higher than 50% in the OEM-Low treatment, and no difference in the other three treatments. In the last 5 rounds, the investment rate becomes not significantly different from 50% in the OEM-Low treatment, and significantly (proportion test, p-value < 0.01) lower than 50% in the OEM-High, CM-Low and CM-High treatments. These results show that in the OEM-Low treatment, at the beginning, subjects have a high investment rate, at the end, they reduced their investment rate. In the OEM-High, CM-Low and CM-High treatments, at the beginning, subjects started making investment decimos with a randomly 50-50 probability, at the end, they also reduced their investment rate.

These results suggest that subjects' investment decisions may be influenced by the time. We use a logistic regression, where the dependent variable is the binary variable of investment and the independent variable is period, to demonstrate the finding. The regression results are listed in Table 2.5.

$$Invest = \beta_0 + \beta_1 Period \tag{2.14}$$

Table 2.5: Regression Result for β_1 (DV: Invest; IV: Period)

Model Type	OEM-Low	OEM-High	CM-Low	CM-High
Logistic regression	-0.0149	-0.0257^{*}	-0.0413^{**}	-0.0704^{**}
Logistic regression with random effect	-0.0246	-0.0432^{**}	-0.0434^{**}	-0.0761^{**}
Logistic regression with fixed effect	-0.0245	-0.0438^{**}	-0.0435^{**}	-0.0761^{**}

$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$

Table 2.5 displays the coefficients of period for each treatment. Except in the OEM-Low treatment, the period has a significantly negative impact on the investment decision from OEM in the other three treatments. This is strong evidence that the subjects in the OEM-High, CM-Low and CM-High treatments learnt not to make investment as time goes. Theory predicts that the OEM should not invest in the OEM-High, CM-Low and CM-High treatments, and the subjects learned to follow the prediction as time passes. This result suggests that in the treatments where the OEM over invested, they learned to not invest over time. Hence, Hypothesis 2 is rejected.

Then we use a random effect regression, where the dependent variable is the investment decision, and the independent variable is the prior period investment decision, the prior profit of the OEM, and the interaction to investigate whether prior decision and prior profit influence the OEM over invest behavior in the OEM-High, CM-Low and CM-High treatments. The coefficients are shown in Table 2.6.

Table 2.6: Regression Result (DV: Invest; IV: as listed)

Coefficient	OEM-High	CM-Low	CM-High
Prior Investment Decision	0.489	0.402	1.025^{**}
Prior OEM Profit	-0.0007^{*}	-0.0000^{**}	-0.0000
Prior Investment Decision * Prior OEM Profit	0.0007^{*}	0.0005^{+}	0.0006^{**}
Period	-0.0111	-0.0302^{*}	-0.0669^{**}

$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$

Table 2.6 displays that when the OEM has no market power, their investment decisions are impacted by the interaction of prior investment decisions and prior profit. Intuitively, if an OEM makes an investment in the last period, his probability of investment decreases as the profit of the last period decreases, since the profit of no investment is significantly lower than the profit of invest (one-sided Mann-Whitney test p-value < 0.01). In the OEM-High treatment, the impact of prior profit is offset by the positive and negative coefficient from the main effect and interaction effect of prior investment decision and prior profit.

In the process of examining the investment decision, we find that the OEM exhibits the under-investment pattern in OEM-Low and over-investment pattern in the other three treatments. However, the OEM learns to adjust the investment rate towards the theory prediction in the OEM-High, CM-Low and CM-High treatments. And the OEM learns from the previous “mistakes”, which is low profit from the investment decision in the last period, in the CM-Low and CM-High treatments.

2.5.3 OEM and CM respond to the power and do not respond to the investment cost.

In section 2.5.1, when comparing OEM-High versus CM-Low/CM-High, we observe that OEM is performing very differently on the investment decision even if the Nash Equilibrium (Nash, 1951) predicts that they should be the same. To furtherly examine the difference, we take a closer look at the impact of power and cost to the decision of OEM.

In the setting of this article, power is defined as the party, either OEM or CM, that can set up the wholesale price in the supply chain. The change of power is easy to be recognized by both parties, since whoever has the power in the supply chain has the option to decide the wholesale price. The four treatments can be separated into two power types. When OEM has power, the power type is OEM and treatments include OEM-Low and OEM-High. When CM has power, the power type is CM and treatments include CM-Low and CM-High.

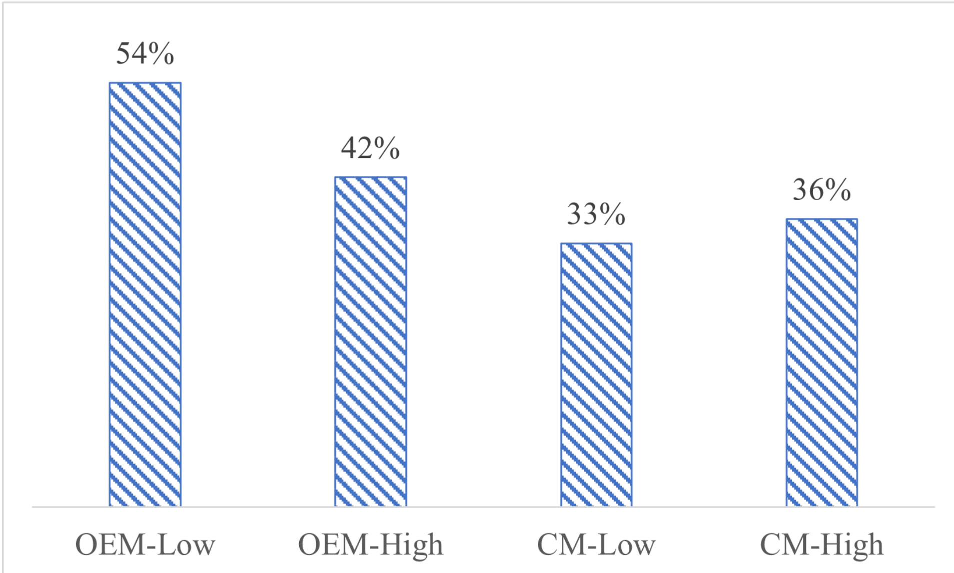
Cost is defined as the investment cost in this setting. In the Nash equilibrium in section 2.3, the theory predicts that there is a threshold of investment cost and when the investment cost is higher or lower than this threshold, the behaviors of both OEM and CM change. The investment cost is visible to both OEM and CM, however, due to the complication of calculation, the investment cost may be vaguer than the power setting to both OEM and CM in the experiment. Based on the difference of investment cost set up, four treatments can be separated into two cost types. When the investment cost is lower than the threshold, the cost type is Low and the treatments include OEM-Low and CM-Low. When the investment cost is higher than the threshold, the cost type is High and treatments include OEM-High and CM-High.

Since the sample size in all treatments is the same, the expected value in each power type or cost type can be easily calculated by taking the average. According to the calibration table in Table 2.12, the average investment percentage when power type is OEM, (OEM-Low and OEM-High) is 50%. The average investment percentage when power type is CM, (CM-Low and CM-High) is 0%. There is a difference in investment percentage between different power types. Same thing happens between different cost types. In Table 2.12, the average investment percentage when cost type is Low, (OEM-Low and CM-Low) is 50%. The average investment percentage when cost type is High, (OEM-High and CM-High) is 0%. There is also a difference in investment percentage between different cost types.

What we discussed above are the equilibrium and calibration numbers. What happens in the experiment? The graph of investment percentage in Figure 2.1 has some indication that the gap is actually smaller than the equilibrium predicts. Based on the summary statistics in Table 2.3, the average investment percentage when power type is OEM is equal to 48% and, when power type is CM, the investment percentage is equal to 35%. The investment percentage, when cost type is Low, is 43% and when cost type is High, the investment percentage is 39%. Based on these averages, the gap between different power types is larger than the gap between different cost types.

To further test the effect of different power types and different cost types, we create two dummy variables, one for the power dummy and one for the cost dummy. The power dummy is set to be 1 if the power type is OEM and 0 if the power type is CM. Therefore, treatments OEM-Low and OEM-High both have the power dummies that are equal to 1 and CM-Low

Figure 2.1: Investment Percentage



and CM-High both have the power dummies that are equal to 0. The cost dummy is set to be 1 if the investment cost type is High and 0 if the cost type is Low. The treatments, OEM-High and CM-High, have the cost dummies that are equal to 1 and the OEM-Low and CM-Low have the cost dummies that are equal 0.

We then use the following random effect regression model to estimate two dummies.

$$\begin{aligned} Invest_{it} &= \beta_0 + \beta_1 Power\ dummy_{it} + \beta_2 Cost\ dummy_{it} \\ &+\beta_3 Power\ dummy_{it} * Cost\ dummy_{it} + a_i + u_{it} \end{aligned} \tag{2.15}$$

Table 2.7: Regression Result (DV: Listed in columns; IV: Listed in rows)

Coefficient	Invest	Quantity of OEM (Q_o)	Quantity of CM (Q_c)
Power dummy(β_1)	1.00^{+}	16.09^{**}	7.89
Cost dummy(β_2)	-0.70	6.79	5.00
Interaction(β_3)	0.83	-2.27	-16.81

$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$

In Table 2.7, the regression result is listed. We listed the regression result from which the dependent variable is Invest, in the second column. The coefficient of power dummy (β_1)

is significantly different from zero at 10% significance level. This coefficient indicates that, when the cost dummy is equal to 0, meaning that if we compare between OEM-Low and CM-Low, the investment percentage is significantly different. And based on Nash Equilibrium, the equilibrium investment percentage is 100% in OEM-Low and 0% in the CM-Low. The equilibrium predicts that the difference of investment percentage between OEM-Low and CM-Low should be significant, meaning that the coefficient of power dummy (β_1) should be significantly positive. The random effect regression result matches the equilibrium prediction since the coefficient of power dummy is significantly positive (with one-sided p value less than 5%).

When cost dummy equals 1, the coefficient of power dummy (β_1) and interaction coefficient (β_3) together measures the difference in investment percentage between OEM-High and CM-High. The Nash equilibrium predicts the investment percentage in both treatments should be 0%. However, since both β_1 and β_3 are positive and β_1 is significant, there is a significant difference in investment percentage between OEM-High and CM-High. Combining previous results, the regression result indicates there is significant difference in investment when power changes.

When the power dummy equals 0, the coefficient of cost dummy (β_2) measures the difference in the investment percentage between CM-Low and CM-High. The Nash Equilibrium predicts that the equilibrium investment percentage in CM-Low and CM-High are both 0%.

The result of the random effect model (in Table 2.7) matches our finding from the graph. The power dummy significantly changes the investment percentage. The coefficient of dummy is 1.00 and this indicates that, when the OEM has the power (power dummy = 1), the investment percentage is significantly increasing. Hypothesis 3a is supported at 10%

significance level. The investment cost dummy is not significant, and this indicates that the investment cost has no significant impact on the investment percentage. Hypothesis 3b is not supported. These conclusions indicate that when power changes, the investment behavior has significantly changed. However, the behavior has no change when the investment cost changes.

To further test this effect, we continue to run other two behavior decisions, OEM order quantity and CM order quantity, using the power dummy and investment cost dummy. The result of both random effect regression models is showing in Table 2.7 in the third and the fourth column. As of the impacts to the decision of OEM, the power dummy is significantly impacting the quantity ordering behaviors by OEM. The cost dummy has no significant impacts on the decisions of OEM. However, neither power dummy nor cost dummy has any impacts on the behavior decisions of CM.

To conclude this section, behavior decisions of OEM, both investment decision and order quantity decision, are significantly impacted by the power but not impacted by the cost. This indicates that, when the power switch from OEM to CM, the OEM reacts significantly to these power switches. However, CM does not significantly respond to power changes. When power changes from OEM to CM, there is no significant change in the decision of CM on order quantity. What is interesting is that, neither OEM nor CM is responding to the investment cost change. When the investment cost changes from low cost to high cost, there is no significant difference in the behavior decisions of neither OEM nor CM. In general, power switch significantly changes the behavior of OEM but not CM. Investment cost has no impacts on the behavior of neither OEM nor CM.

2.5.4 In the perspective of the entire supply chain, investment always benefits the entire supply chain.

In the perspective of the entire supply chain, investment always benefits the entire supply chain. By looking at the Nash Equilibrium (Nash, 1951), we find the conclusion that the investment only helps when the OEM has power and the investment cost is lower than the threshold, and the investment is going to harm the OEM in other cases. But what about the entire supply chain? In theory, Nash Equilibrium (Nash, 1951) predicts that the invest is the equilibrium decision in all four treatments, if the entire supply chain is considered as a one player. Using the same set of numbers in the calibration also confirms that the profit for the supply chain is always higher when the OEM decides to invest.

To answer this question, we look at two types of measurements. The first one is the profit of the entire supply chain. This profit is calculated by summing up the Profit of OEM and CM in both invest and not invest condition. To study the benefit of investing in the supply chain in our experiment setting, we use the same set of parameters in the calibration table to calculate the sum of Profit of OEM and CM and the result is summarized in the Table 2.8.

As shown in Table 2.8, the sum of Profit of OEM and CM in the invest situation is always higher than the profit in the no invest situation. Recall the Nash Equilibrium (Nash, 1951) in section 2.3, the equilibrium predicts that investment is only beneficial to OEM in the OEM-Low treatment. Here, this table means that in all four treatments, the investment is beneficial to the entire supply chain. Therefore, considering the entire supply chain, the investment is beneficial in all four treatments.

The second type of measurement is the channel efficiency. To calculate the channel efficiency, the centralized supply chain profit needed to be calculated first. The centralized supply chain profit is calculated based on if the entire supply chain (OEM and CM) is acting as one company/player. The centralized Profit of Supply Chain (π^*_{SC}/π^*_{SCI}) can be calculated using Nash Equilibrium (Nash, 1951) and the detailed solution is in Appendix A. The Nash Equilibrium (Nash, 1951) illustrates that the investment decision is, again, a threshold solution, meaning that, if investment cost is less than the threshold ($I^*_{Centralized}$) in equation (2.16), the OEM should invest. And comparing the threshold of investment in the decentralized and centralized supply chain, if the condition (2.17) is satisfied, the threshold of investment in the centralized supply chain (I^*_{Cen}) will be higher than the threshold in the decentralized supply chain (I^*_{Decen}). Intuitively, it means that, under the condition of equation (2.17), the OEM should have a higher tolerance of investment cost in order to invest if the supply chain is centralized.

$$I^*_{Cen} = \frac{(c_I^2 - c^2 - 2ac_I + 2ac)}{4b} \tag{2.16}$$

$$-10a + 5c_I + 5c + 8c_M < 0 \tag{2.17}$$

Using the same set of calibration numbers that we proposed in the experiment design, we can calculate that both low cost (380) and high cost (580) are lower than the I^*_{Cen}. Therefore, the equilibrium solution for the centralized supply chain in this setting is invest, which means, in theory, investment is always beneficial to the centralized supply chain. The calibration number can also be used to calculate the sum of equilibrium profit of OEM and CM in both invest and not invest situations and the result is shown in Table 2.8. The numerical results also confirm that investment is a beneficial decision of the entire supply chain in both centralized and decentralized supply chains in our experiment design setting. The supply chain efficiency can be calculated by using the sum of the OEM and CM profit, in both invest (Table 2.8 row 1) and not invest (Table 2.8 row 2) situations, divided by the centralized supply chain profit (Table 2.8 row 3). It is clear that the investment generates higher channel efficiency. The investment can coordinate the supply chain better.

Table 2.8: Equilibrium Channel profit

		OEM-Low	OEM-High	CM-Low	CM-High
Profit of Supply Chain	Invest(1)	1981.11	1781.11	2088	1888
(Profit OEM+ Profit CM)	Not Invest(2)	1494.44	1494.441	1530.5	1530.5
Profit of Centralized Supply	Invest(3)	2432.5	2232.5	2432.5	2232.5
Chain (π^*_{SCI}/π^*_{SC})	Not Invest(4)	1800	1800	1800	1800
Equilibrium Channel	Invest$\frac{(1)}{(3)}$	81.44%	79.78%	85.84%	84.57%
Efficiency	Not Invest $\frac{(2)}{(4)}$	61.44%	66.94%	62.92%	68.56%

What we just discussed is the theory prediction and what happened in the experiment? Given the off-equilibrium decisions that subjects make in the experiment, is investment still beneficial to the entire supply chain?

Table 2.9: Observed Channel profit

		OEM-Low	OEM-High	CM-Low	CM-High
Profit of Supply Chain	Invest	1156	1352	1531	1198
(Profit OEM+ Profit CM)	Not Invest	-67	1146	1109	885
Observed Channel	Invest	48%	61%	63%	54%
Efficiency	Not Invest	-3%	51%	46%	40%

Table 2.9 shows the observed channel profit. In the experiment, even if the subjects are not able to pick the equilibrium decisions (wholesale price, quantity of OEM, quantity of CM), the channel profit they obtained still exhibits the same pattern as the Nash Equilibrium (Nash, 1951) predicts. The channel profit in the invest situation is significantly (with the one-sided Mann-Whitney test p value less than 0.01) higher than the channel profit in the not invest situation in all four treatments. Hypothesis 4a is supported at 5% significance level.

Table 2.9 also shows the observed channel efficiency in the experiments. The One-sided Mann-Whitney test is used to test if the channel efficiency is significantly higher when OEM decides to make investment. In all four tests, the p-values are all less than 0.05, so the channel efficiency is also higher in all four treatments when OEM decides to invest. Hypothesis 4b is supported at 5% significance level.

In the previous section, Nash Equilibrium (Nash, 1951) predicts that investment is considered as only beneficial to the OEM when the OEM has power and the investment cost is in the lost cost condition of the experiment design. However, what we found in this section is that, under both conditions of investment cost (both low and high cost in the experiment design), the investment is beneficial to the entire supply chain, regardless who has the market power. In general, the investment is beneficial to the entire supply chain, both in the measurement of raw profit and channel efficiency. The meaning behind this conclusion is that investment, which is considered as the loss of money in the supply chain, can actually be more beneficial to the entire supply chain.

2.5.5 OEM set wholesale price lower than best response, while CM set the wholesale price higher than best response.

After the investment decision, we look at the 2nd decision that the subjects make — the wholesale price. Depending on the treatments, the wholesale price is either set by the OEM or by the CM. Thus, our discussion of wholesale price will be separated by two sections. One is when the OEM has the power to set up the wholesale price and another is when CM has the power to set up the wholesale price.

When OEM has the power to set up the wholesale price, the OEM would try to set the wholesale price as low as possible, as the lower wholesale price would give a higher profit for the OEM. The investment decision from OEM seems to only reduce the production cost of the CM and has no direct benefit towards the OEM. However, since we artificially set the lower bound of the wholesale price to be not lower than the production cost, the investment decision benefits the OEM by being able to set a lower wholesale price if he decides to invest. In the experiment design, the production cost of CM is 40 if OEM decides not to invest and 25 if OEM invests. Thus, if the OEM decides to make investment to CM, he could get benefit by being able to set the wholesale price down to 25, instead of 40. Therefore, when OEM has the power to set up the wholesale price, the best response wholesale price towards his own investment decision is 25, if he decides to invest, and 40, if he decides not to invest.

When CM has the power to set up the wholesale price, CM would prefer not to set a low wholesale price, since the wholesale price contributes to the profit of CM. But a too high wholesale price also reduces the quantity of OEM. Thus the best response wholesale price based on the investment decision of OEM can be found using the equation (2.54) in

Appendix A.

Table 2.10 presents the best response wholesale price and observed wholesale price from the experiment. In the table, the + sign means the difference between the observed value and theoretical best response is positive. We can tell from the table that, when OEM has the power to set up the wholesale price, under both invest and not invest decisions, OEM sets the wholesale price significantly higher than the theoretical best response wholesale price. When CM has the power to set up the wholesale price, CM sets the wholesale price significantly lower than the theoretical best response wholesale price.

Table 2.10: Wholesale price result

		OEM-Low	OEM-High	CM-Low	CM-High
Observed Value	Invest	36.44	34.59	63.16	59.50
	Not Invest	49.96	44.97	76.59	84.53
Best Response	Invest	25	25	62	62
	Not Invest	40	40	69.5	69.5
Difference(Observed Value-Best Response)	Invest	$+^{**}$	$+^{**}$	$-^{**}$	$-^{**}$
	Not Invest	$+^{**}$	$+^{**}$	$-^{**}$	12.03

$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$

Note: + means the positive difference

We further test if the difference between observed value and best response is the same under both invest and not invest conditions. To examine this effect, we use the dependent variable: observed value – best response value, and the independent variable is the investment dummy variable. The result of the regression is shown in Table 2.11.

The regression result indicates that there is significant difference in wholesale price under

Table 2.11: Regression Result for β_1 (DV: $w_{observed} - w_{bestresponse}$; IV: $Invest$)

Model Type	OEM-Low	OEM-High	CM-Low	CM-High
Regression	1.472635	1.621905	-5.932167	-14.53247^{**}
Regression with random effect	9.6926^{**}	2.8295^{*}	-5.9647	-15.1778^{**}
Regression with fixed effect	11.5812^{**}	3.199074^{**}	-5.984205	-16.66298^{**}
$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01$				

invest and not invest condition. When OEM has the power to set up the wholesale price, in the treatment OEM-Low and OEM-High, the difference between observed wholesale price and best response wholesale price is significantly higher when OEM decides to invest. Combined with the result in Table 2.11, OEM deviates in the positive way further from the best response in setting up the wholesale price when he decides to invest. However, the average of wholesale price under invest situation is still significantly (with Wilcoxon p value equal to 0.0000 in both treatments) lower than 40, which is the best response wholesale price under not invest situation. This means the OEM still gets benefit from the investment decision by being able to set a lower wholesale price, although this benefit is not as big as the best response has. Also, from the Nash Equilibrium equation (2.54) in Appendix A, a higher than best response wholesale price in OEM-Low/OEM-High treatment drives a higher profit of CM. Therefore, the higher-than-best-response wholesale price benefits the CM in these two treatments.

When CM has the power to set up the wholesale price, in CM-Low and CM-High treatment, the difference between observed wholesale price and best response wholesale price is lower when OEM decides to invest. Combined with the result in table 2.11, CM sets the wholesale price significantly lower than the best response value in both treatments and she sets the wholesale price even lower when OEM decides to invest. Due to the equation (2.54) in Appendix A, a lower wholesale price would drive in a higher OEM profit compared with equilibrium. Thus, CM sets a lower-than-best-response wholesale price that also benefits the OEM.

To conclude the above result, when OEM has the power to set up the wholesale price, he sets the wholesale price higher than the best response. He gets some, not all, benefit from the investment decision by setting up a lower wholesale price. And by setting a wholesale price higher than the best response, CM gets some benefits. When CM has the power to set up the wholesale price, she sets a significantly lower wholesale price than the best response and she also sets an even lower wholesale price when OEM decides to invest. This low-than-best-response wholesale price benefits the OEM as well.

2.6 Discussion

In this article, we have two major findings, one in investment and another in wholesale price.

In our setting, we allow the uncontracted investment from OEM to CM. Game theory says OEM should always choose the investment decision beneficial to himself. However, in the experiment, we observe this theory is not always right. In the treatment, in which investment is beneficial to OEM, he does not always choose to invest. In other treatments, where investment is not beneficial to OEM, he chooses to invest some of the time. Although in the later treatment, OEM learns not to invest as the period increases, the investment rate never diminishes to 0% at the end. For some reason, bounded rationality or something else, OEM chooses the investment not always beneficial to him and we call it "non-rational behavior." After this, we continue to investigate the benefit of investment to the entire supply chain. From the perspective of the supply chain, the investment is beneficial to the supply chain. Therefore, combining the non-rational behavior and uncontracted investment, the supply chain gets a larger benefit. We propose that this could be a new solution to increase the channel efficiency.

Our second major find is the wholesale price. Game theory predicts the wholesale price is the second decision point to squeeze the profit to the decision maker. In our setting, wholesale price is decided by the party that has power. By setting the wholesale price at the best response point, whoever has the power could maximize his/her profit depending on the investment. However, we find in the experiment that neither OEM nor CM sets the wholesale price at the best response point. More than that, they even set the wholesale price that is beneficial to their competitors. We refer to this as the "being-nice behavior." This behavior reacts to the investment decision. CM is being nicer to OEM, by setting a lower wholesale price, when OEM invests. This behavior could be a returning favor for the non-rational behavior of OEM and furtherly lubricates the supply chain.

2.7 Conclusion and Future Research

In this article, we have proposed a setting of a supply chain with a dual channel setting. Two major players are in the supply chain, which are OEM and CM. OEM and CM have a relationship, both as manufacturer and retailer and also as competitors to each other. CM manufactures the product for OEM and also sells the product in the end market to compete with OEM. On top of this dual channel setting, we add an investment option to the OEM.

This investment could reduce the production cost of CM. Meanwhile, market power, which defines the player that can set the wholesale price, is introduced in the model. We would like to examine the impacts towards the investment decision by changing investment cost and switching market power.

Based on the initial model setting, we solved the Nash Equilibrium (Nash, 1951) for the investment decision. The equilibrium, depending on the market power, is different. When OEM has the market power, the investment decision is a threshold strategy. It means that, if the investment cost is lower than a threshold, the equilibrium decision for OEM is to invest. If the investment cost is higher than that threshold, the equilibrium decision for OEM is not to invest. When CM has the market power to set up the wholesale price, the equilibrium decision for OEM, regardless of investment cost, is not to invest.

Based on the equilibrium, we build a 2 by 2 experiment design. The first changing element is the market power and treatments are separated into OEM-power and CM-power. The second changing element is investment cost. Based on the threshold calculated equilibrium, treatments are separated into high and low cost. High cost stands for the investment cost higher than the threshold calculated by the equilibrium and low cost stands for lower than threshold. Therefore, four treatments are named OEM-Low, OEM-High, CM-Low and CM-High, where the first word represents the market-power holding player and the second word represents the investment cost high or low. The behavior experiment is conducted in the behavior lab in the university with undergraduate business students. The experiment is using between-group experiment design and each subject only participates in one treatment. Each treatment has around 24 subjects and each subject is randomly assigned to play one role, either OEM or CM, in the experiment. The experiment proceeds for 30 periods. The role for each subject is fixed but they are randomly grouped in each period.

From the behavior experiment, we have found several interesting observations. The first one is the investment behavior in the treatments. The subject behaves off-equilibrium sometime in the experiment. In the treatment that has the equilibrium decision is to invest, OEM-Low, we observe the under-investing behavior in this treatment, which means that the subjects do not invest all the time in this treatment. In the other three treatments, which have the equilibrium decision not to invest, we observe the over-investing behavior in this treatment. This means subjects in the other three treatments do invest some time. However, the proportion test and logit regression indicate that the subjects in these treatments, OEM-High, CM-Low and CM-High, start the treatment by 50/50 investment rate and then their investment rate significantly decreases as the period increases. The subjects learn not to invest, which is the equilibrium, over time.

The second observation we have are the impacts of power and cost. The four treatments are built from a 2 by 2 experiment design, with one changing measurement is market power and another one is investment cost. The equilibrium predicts that by changing either market power or the investment cost, the equilibrium decision will be changed. In order to test these impacts, we create two dummy variables to represent market power and investment cost. The logit random effect model indicates that the market power significantly changes the investment decision, while the investment cost has no significant impacts on the investment decisions. The change of market power is more sensitive to being caught by the subject, in terms of changing their investment decisions. The investment cost, on the other hand, is more hidden in the experiment and the subjects are less sensitive to this variation. This observation illustrates that market power, compared with investment cost, has a major impact towards the investment decision. Therefore, when OEM has the market power, it impacts his investment decision.

The third observation is that the investment is better for the supply chain. In the Nash Equilibrium, the investment is considered to be beneficial only in one treatment, which is only in OEM-Low. However, if the entire supply chain is considered, the investment is a more beneficial decision for the supply chain. Comparing the profit of the entire supply chain in both situations when OEM decide to invest versus not to invest, the supply chain profit is always higher in the invest situation. This higher difference both exists in the equilibrium and also is significant in the experiment observation. An investment not only benefits the supply chain in the aspect of raw profit, but also in the aspect of supply chain efficiency. The supply chain efficiency is significantly higher in all treatments if the OEM decides to invest. What managers can learn from this article is that, by introducing a cost-reducing investment from OEM to CM, the supply chain efficiency can be increased. The supply chain can benefit from this investment option.

The last observation we have from the experiment is the wholesale price. Both OEM and CM never set the wholesale price at the equilibrium, nor the best response wholesale price. And also the bias is on either the positive or negative side, depending on market power. When OEM has the power to set up the wholesale price, he sets the wholesale price significantly higher than the best response wholesale price, which results in more benefits for the CM. And this bias changes significantly when his investment decision changes. When CM has the power to set up the wholesale price, she sets the wholesale price significantly lower than the best response wholesale price. This low wholesale price benefits the OEM profit. Also, the bias of wholesale price changes when the investment decision of OEM changes.

In general, we find the off-equilibrium behavior in the uncontracted investment. And we also tested that the investment is beneficial for the entire supply chain. Therefore, the non-rational behavior in investment helps the supply chain in the experiment. This could be a new solution to increase the channel efficiency. The same off-equilibrium behavior in wholesale price illustrates the being-nice behavior from the power holding player. Subjects are not just bounded rational in the experiment. They are expressing kindness to their competitors. This could be a lubricator for the supply chain.

In this article, we only test the dual channel setting with a simple wholesale price contract. In the future, different contract types can be added in the model to test if an even higher supply chain efficiency can be achieved by using other contract types.

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2.9 Chapter 2 Appendix

2.9.1 Chapter 2 Appendix A Proof

2.9.1.1 Nash Equilibrium Solutions: when OEM has power.

Not Invest

$$\pi_{OEM} = (P - w) \cdot Q_o = (a - b(Q_o + Q_c) - w) * Q_o \tag{2.18}$$

$$\begin{aligned}\pi_{CM} &= (P - c - c_m) \cdot Q_c + (w - c) \cdot Q_o \\ &= (a - b(Q_o + Q_c) - c - c_m) \cdot Q_c + (w - c) \cdot Q_o\end{aligned} \tag{2.19}$$

$$\frac{d\pi_{OEM}}{dQ_o} = a - 2b \cdot Q_o - b \cdot Q_c - w \tag{2.20}$$

$$\frac{d\pi_{CM}}{dQ_c} = a - b \cdot Q_o - 2b \cdot Q_c - c - c_m \tag{2.21}$$

Let $Q_o^* = argmax(\pi_{OEM})$ and $Q_c^* = argmax(\pi_{CM})$,

$$Q_o^* = \frac{a - b \cdot Q_c - w}{2b} \tag{2.22}$$

$$Q_c^* = \frac{a - b \cdot Q_o - c - c_m}{2b} \tag{2.23}$$

So,

$$Q_o^* = \frac{a - 2w + c + c_m}{3b} \tag{2.24}$$

$$Q_c^* = \frac{a - 2c - 2c_m + w}{3b} \tag{2.25}$$

Let $\pi_{OEM}^* = max(\pi_{OEM})$,

$$\pi_{OEM}^* = \frac{1}{9b}(a + c + c_m - 2w)^2 \tag{2.26}$$

$$\frac{d\pi_{OEM}}{dw} = -\frac{4}{9b}(a + c + c_m - 2w) \tag{2.27}$$

Let $w^* = argmax(\pi_{OEM})$

$$w^* = \frac{a + c + c_m}{2} \tag{2.28}$$

Since $c < w$, when $w^* = c$, π_{OEM} will be the equilibrium.

$$\pi_{OEM}^* = \frac{1}{9b}(a - c + c_m)^2 \tag{2.29}$$

Invest

$$\pi_{OEMI} = (P_I - w_I) \cdot Q_{oI} = (a - b(Q_{oI} + Q_{cI}) - w) * Q_{oI} - I \tag{2.30}$$

$$\begin{aligned} \pi_{CMI} &= (P_I - c_I - c_m) \cdot Q_{cI} + (w_I - c_I) \cdot Q_{oI} \\ &= (a - b(Q_{oI} + Q_{cI}) - c_I - c_m) \cdot Q_{cI} + (w_I - c_I) \cdot Q_{oI} \end{aligned} \tag{2.31}$$

$$\frac{d\pi_{OEMI}}{dQ_{oI}} = a - 2b \cdot Q_{oI} - b \cdot Q_{cI} - w_I \tag{2.32}$$

$$\frac{d\pi_{CMI}}{dQ_{cI}} = a - b \cdot Q_{oI} - 2b \cdot Q_{cI} - c_I - c_m \tag{2.33}$$

Let $Q_{oI}^* = argmax(\pi_{OEMI})$ and $Q_{cI}^* = argmax(\pi_{CMI})$,

$$Q_{oI}^* = \frac{a - b \cdot Q_{cI} - w_I}{2b} \tag{2.34}$$

$$Q_{cI}^* = \frac{a - b \cdot Q_{oI} - c_I - c_m}{2b} \tag{2.35}$$

So,

$$Q_{oI}^* = \frac{a - 2w_I + c_I + c_m}{3b} \tag{2.36}$$

$$Q_{cI}^* = \frac{a - 2c_I - 2c_m + w_I}{3b} \tag{2.37}$$

Let $\pi_{OEMI}^* = max(\pi_{OEMI})$,

$$\pi_{OEMI}^* = \frac{1}{9b}(a + c_I + c_m - 2w_I)^2 \tag{2.38}$$

$$\frac{d\pi_{OEMI}}{dw_I} = -\frac{4}{9b}(a + c_I + c_m - 2w_I) \tag{2.39}$$

Let $w_I^* = argmax(\pi_{OEMI})$

$$w_I^* = \frac{a + c_I + c_m}{2} \tag{2.40}$$

Since $c < w_I$, when $w_I^* = c_I$, π_{OEMI} will be the equilibrium.

$$\pi_{OEMI}^* = \frac{1}{9b}(a - c_I + c_m)^2 - I \tag{2.41}$$

The condition that OEM would invest is when $\pi_{OEMI}^* > \pi_{OEM}^*$, that is

$$\frac{1}{9b}(a - c_I + c_m)^2 - I > \frac{1}{9b}(a - c + c_m)^2 \tag{2.42}$$

The condition that OEM would invest is

$$I < \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I)) \tag{2.43}$$

2.9.1.2 Nash Equilibrium Solutions: when CM has power.

Not Invest

$$\pi_{OEM} = (P - w) \cdot Q_o = (a - b(Q_o + Q_c) - w) \cdot Q_o \tag{2.44}$$

$$\begin{aligned} \pi_{CM} &= (P - c - c_m) \cdot Q_c + (w - c) \cdot Q_o \\ &= (a - b(Q_o + Q_c) - c - c_m) \cdot Q_c + (w - c) \cdot Q_o \end{aligned} \tag{2.45}$$

$$\frac{d\pi_{OEM}}{dQ_o} = a - 2b \cdot Q_o - b \cdot Q_c - w \tag{2.46}$$

$$\frac{d\pi_{CM}}{dQ_c} = a - b \cdot Q_o - 2b \cdot Q_c - c - c_m \tag{2.47}$$

Let $Q_o^* = argmax(\pi_{OEM})$ and $Q_c^* = argmax(\pi_{CM})$,

$$Q_o^* = \frac{a - b \cdot Q_c - w}{2b} \tag{2.48}$$

$$Q_c^* = \frac{a - b \cdot Q_o - c - c_m}{2b} \tag{2.49}$$

So,

$$Q_o^* = \frac{a - 2w + c + c_m}{3b} \tag{2.50}$$

$$Q_c^* = \frac{a - 2c - 2c_m + w}{3b} \tag{2.51}$$

Let $\pi_{CM}^* = max(\pi_{CM})$,

$$\pi_{CM}^* = \frac{1}{9b}(a - 2c - 2c_m + w)^2 + \frac{1}{3b}(w - c)(a - 2w + c + c_m) \tag{2.52}$$

$$\frac{d\pi_{CM}}{dw} = -\frac{1}{9b}(5a + 5c - c_m - 10w) \tag{2.53}$$

Let $w^* = argmax(\pi_{CM})$

$$w^* = \frac{5a + 5c - c_m}{10} \tag{2.54}$$

Since $c < w^* < P$, when $w^* = \frac{5a+5c-c_m}{10}$, π_{CM} will be the equilibrium.

$$\begin{gathered} \pi^*_{CM} = \frac{5a^2 - 10ac - 10ac_m + 5c^2 + 10cc_m + 9c_m^2}{20b} \\ \pi^*_{OEM} = \frac{4c_m^2}{25b} \end{gathered} \tag{2.55}$$

Invest

$$\pi_{OEMI} = (P_I - w_I) \cdot Q_{oI} = (a - b(Q_{oI} + Q_{cI}) - w) \cdot Q_{oI} - I \tag{2.56}$$

$$\begin{aligned} \pi_{CMI} &= (P_I - c_I - c_m) \cdot Q_{cI} + (w_I - c_I) \cdot Q_{oI} \\ &= (a - b(Q_{oI} + Q_{cI}) - c_I - c_m) \cdot Q_{cI} + (w_I - c_I) \cdot Q_{oI} \end{aligned} \tag{2.57}$$

$$\frac{d\pi_{OEMI}}{dQ_{oI}} = a - 2b \cdot Q_{oI} - b \cdot Q_{cI} - w_I \tag{2.58}$$

$$\frac{d\pi_{CMI}}{dQ_{cI}} = a - b \cdot Q_{oI} - 2b \cdot Q_{cI} - c_I - c_m \tag{2.59}$$

Let $Q^*_{oI} = argmax(\pi_{OEMI})$ and $Q^*_{cI} = argmax(\pi_{CMI})$,

$$Q^*_{oI} = \frac{a - b \cdot Q_{cI} - w_I}{2b} \tag{2.60}$$

$$Q^*_{cI} = \frac{a - b \cdot Q_{oI} - c_I - c_m}{2b} \tag{2.61}$$

So,

$$Q_{oI}^* = \frac{a - 2w_I + c_I + c_m}{3b} \tag{2.62}$$

$$Q_{cI}^* = \frac{a - 2c_I - 2c_m + w_I}{3b} \tag{2.63}$$

Let $\pi_{CMI}^* = max(\pi_{CMI})$,

$$\pi_{CMI}^* = \frac{1}{9b}(a - 2c_I - 2c_m + w_I)^2 + \frac{1}{3b}(w_I - c_I)(a - 2w_I + c_I + c_m) \tag{2.64}$$

$$\frac{d\pi_{CMI}}{dw_I} = -\frac{1}{9b}(5a + 5c_I - c_m - 10w_I) \tag{2.65}$$

Let $w_I^* = argmax(\pi_{CMI})$

$$w_I^* = \frac{5a + 5c_I - c_m}{10} \tag{2.66}$$

Since $c_I < w_I^* < P$, when $w_I^* = \frac{5a+5c_I-c_m}{10}$, π_{CMI} will be the equilibrium.

$$\begin{gathered} \pi_{CMI}^* = \frac{5a^2 - 10ac_I - 10ac_m + 5c_I^2 + 10c_Ic_m + 9c_m^2}{20b} \\ \pi_{OEMI}^* = \frac{4c_m^2}{25b} - I \end{gathered} \tag{2.67}$$

Since $\frac{4c_m^2}{25b} - I < \frac{4c_m^2}{25b}$,

$$\pi_{OEMI}^* < \pi_{OEM}^* \tag{2.68}$$

2.9.1.3 Nash Equilibrium Solutions: centralized supply chain.

Not Invest

$$\pi_{SC} = (P - c) \cdot Q_{SC} = (a - b \cdot Q_{SC} - c) \cdot Q_{SC} \tag{2.69}$$

$$\frac{d\pi_{SC}}{dQ_{SC}} = a - 2b \cdot Q_{SC} - c \tag{2.70}$$

Let $Q^*_{SC} = argmax(\pi_{SC})$,

$$Q^*_{SC} = \frac{a-c}{2b} \tag{2.71}$$

Let $\pi^*_{SC} = max(\pi_{SC})$,

$$\pi^*_{SC} = \frac{(a-c)^2}{4b} \tag{2.72}$$

Invest

$$\pi_{SCI} = (P_I - c_I) \cdot Q_{SCI} = (a - b \cdot Q_{SCI} - c_I) \cdot Q_{SCI} - I \tag{2.73}$$

$$\frac{d\pi_{SCI}}{dQ_{SCI}} = a - 2b \cdot Q_{SCI} - c_I \tag{2.74}$$

Let $Q^*_{SCI} = argmax(\pi_{SCI})$,

$$Q^*_{SCI} = \frac{a-c_I}{2b} \tag{2.75}$$

Let $\pi^*_{SCI} = max(\pi_{SCI})$,

$$\pi^*_{SCI} = \frac{(a-c_I)^2}{4b} - I \tag{2.76}$$

The condition that OEM (now is also the centralized supply chain) would invest is when $\pi^*_{SCI} > \pi^*_{SC}$, that is

$$\frac{(a-c_I)^2}{4b} - I > \frac{(a-c)^2}{4b} \tag{2.77}$$

The condition that OEM (now is also the centralized supply chain) would invest is

$$I < \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b} \tag{2.78}$$

2.9.1.4 Comparing the centralized and de-centralized supply chain.

Let I^*_{DeCen} = threshold for OEM to invest in the de-centralized supply chain I^*_{Cen} =threshold for OEM to invest in the centralized supply chain

$$I^*_{DeCen} = \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I)) \tag{2.79}$$

$$I_{Cen} = \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b} \tag{2.80}$$

So,

$$\begin{aligned} I^*_{DeCen} - I^*_{Cen} &= \frac{1}{9b}(c_I^2 - c^2 + 2(a + c_m)(c - c_I)) - \frac{c_I^2 - c^2 - 2ac_I + 2ac}{4b} \\ &= \frac{(c - c_I)(-10a + 5c_I + 5c + 8c_m)}{36b} \end{aligned} \tag{2.81}$$

The condition that de-centralized investment threshold is less than centralized investment threshold ($I^*_{DeCen} < I^*_{Cen}$) is when

$$-10a + 5c_I + 5c + 8c_m < 0 \tag{2.82}$$

2.9.2 Chapter 2 Appendix B Calibrations

Table 2.12: Parameter Calibration

	OEM-Low	OEM-High	CM-Low	CM-High
Investment cost(I)	380	580	380	580
I^*	483.33	483.33	–	–
Production cost before investment (c)	40	40	40	40
Production cost after investment (c_I)	25	25	25	25
Investment Percentage	100%	0%	0%	0%
Quantity of OEM (Q_o^*/Q_{oI}^*)	53	43	4	4
Quantity of CM (Q_c^*/Q_{cI}^*)	43	33	53	53
Wholesale Price (w^*/w_I^*)	25	40	69.5	69.5
Market Price (P^*)	51.67	61.67	71.5	71.5
Profit of OEM (π_{OEM}^*/π_{OEMI}^*)	1042.22	938.89	8	8
Profit of CM (π_{CM}^*/π_{CMI}^*)	938.89	555.56	1522.5	1522.5
Profit of Supply Chain ($\pi_{OEM}^* + \pi_{CM}^*/\pi_{OEMI}^* + \pi_{CM}^*$)	1981.11	1494.44	1530.5	1530.5

Table 2.13: Parameter Calibration - Centralized Supply Chain

	Low	High
Investment cost(I)	380	580
I^*	1012.5	1012.5
Production cost before investment (c)	40	40
Production cost after investment (c_I)	25	25
Investment Percentage	100%	100%
Quantity of Supply Chain (Q^*_{SC}/Q^*_{SCI})	75	75
Wholesale Price (w^*/w^*_I)	25	25
Market Price (P^*)	62.5	62.5
Profit of Supply Chain (π^*_{SC}/π^*_{SCI})	2432.5	2232.5

2.9.3 Chapter 2 Appendix C Experiment Screenshots

Figure 2.2: Experiment Screenshots 1

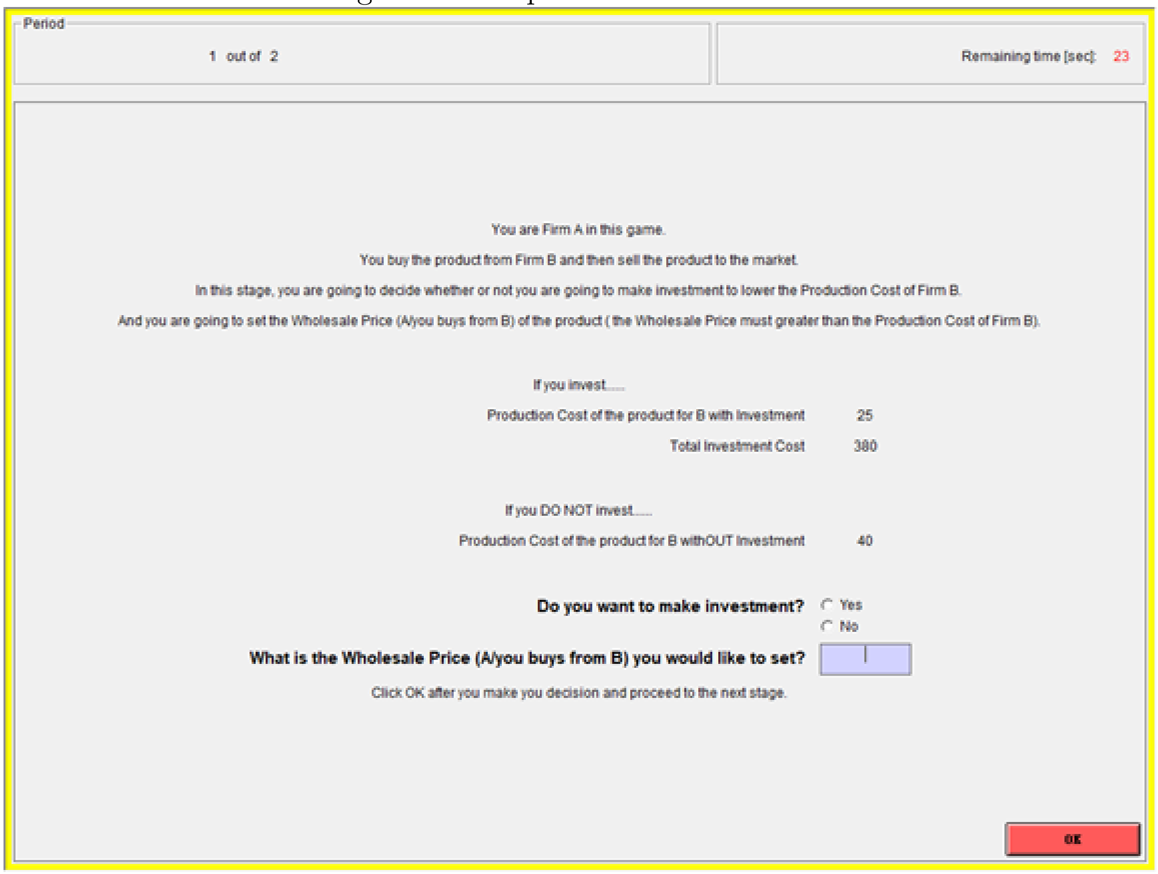


Figure 2.3: Experiment Screenshots 2

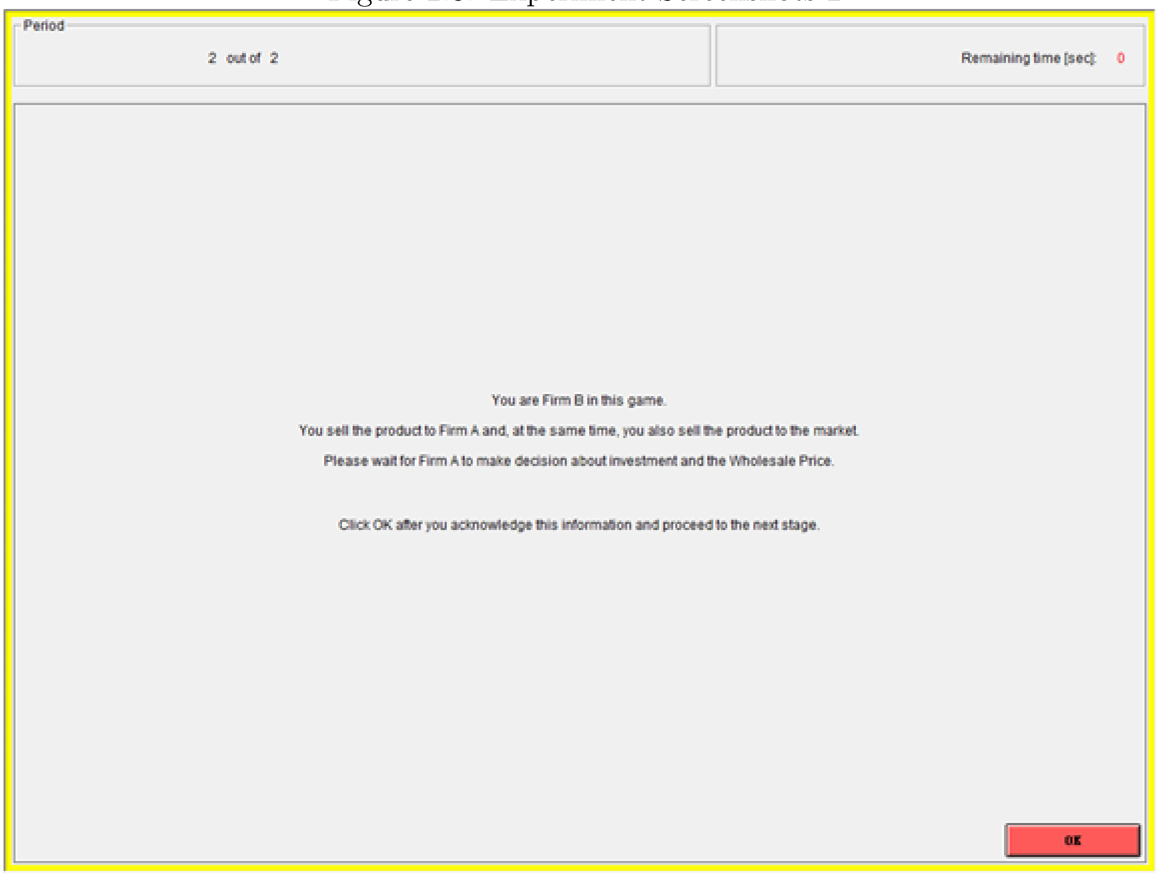


Figure 2.4: Experiment Screenshots 3

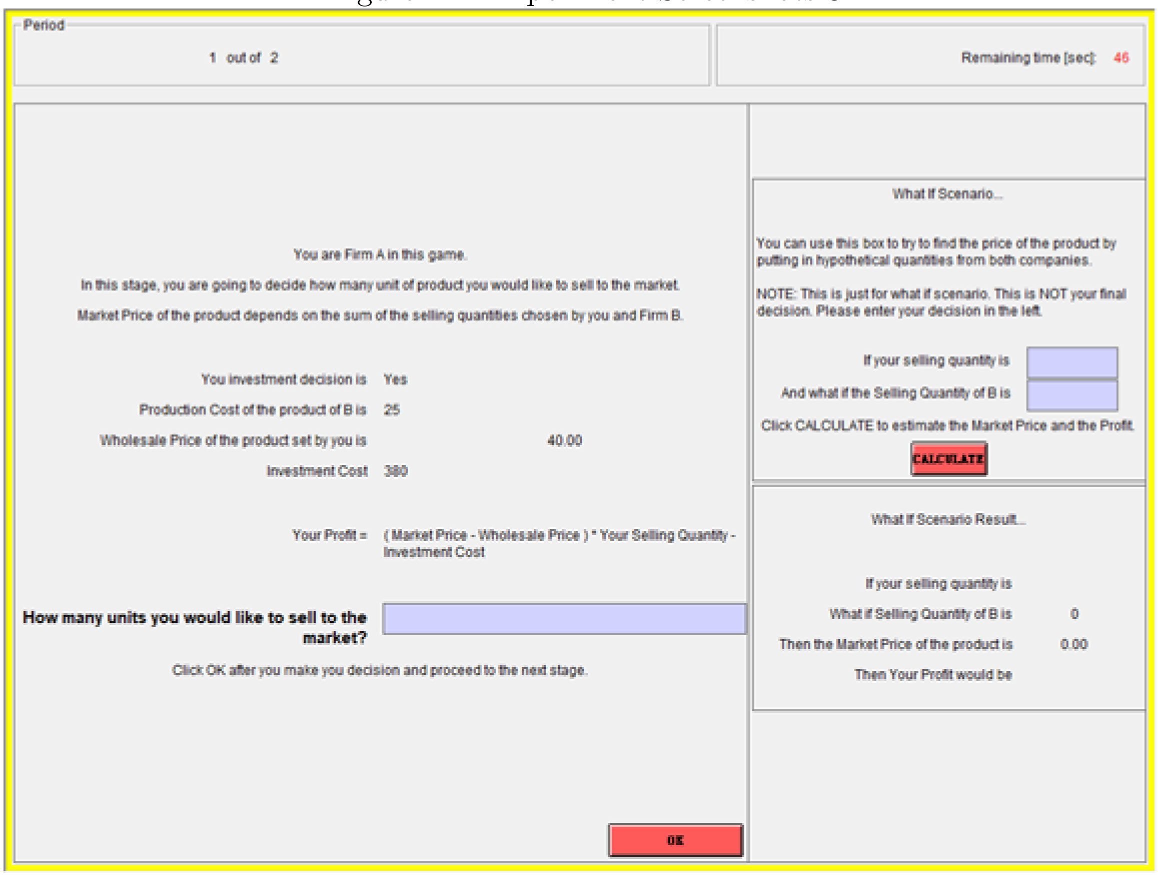


Figure 2.5: Experiment Screenshots 4

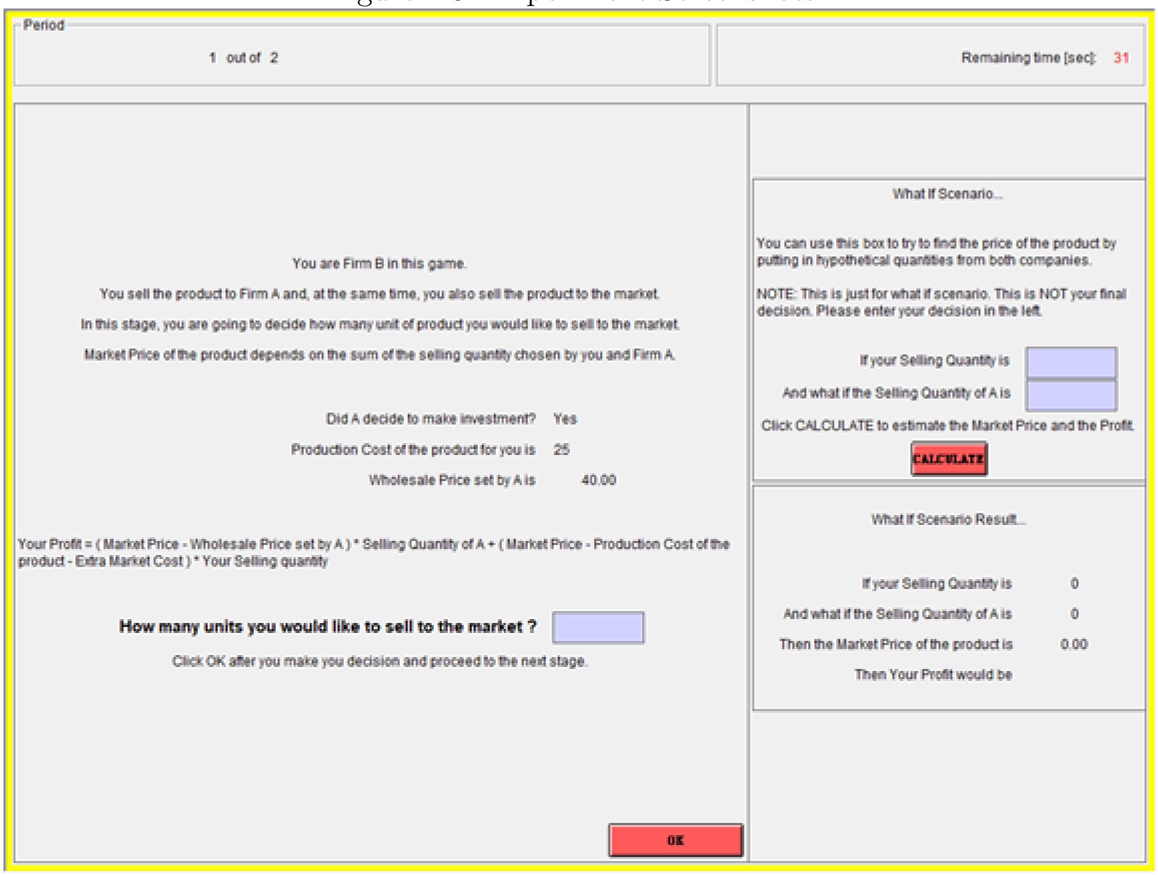


Figure 2.6: Experiment Screenshots 5

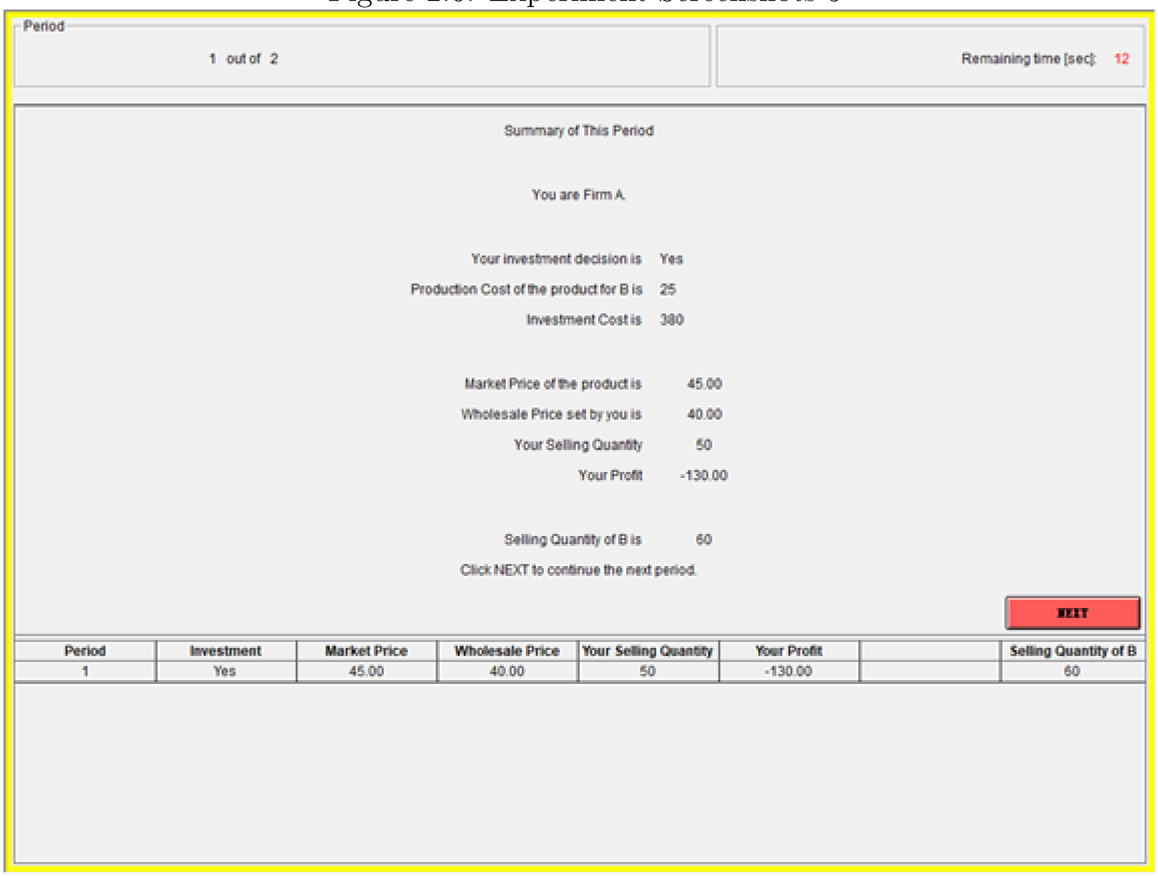
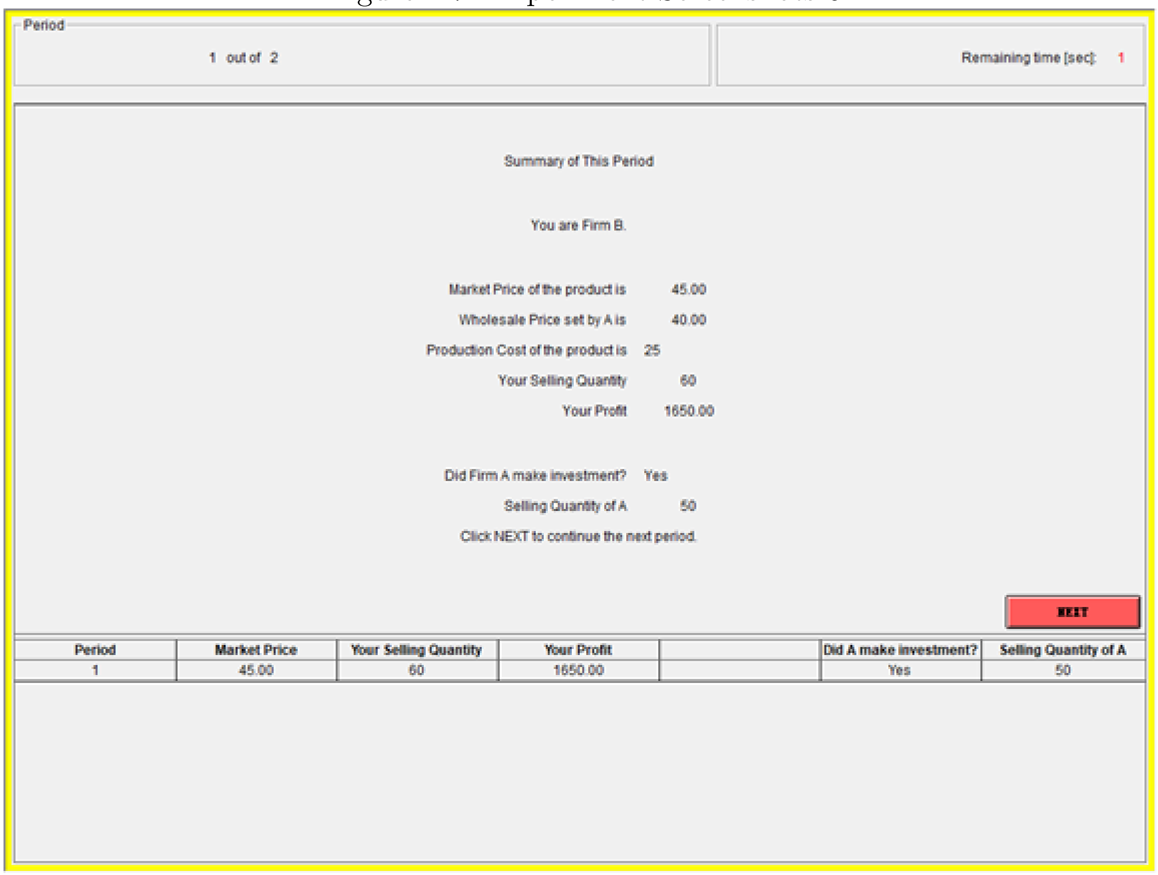


Figure 2.7: Experiment Screenshots 6



CHAPTER 3

An Experimental Study of Market Power in the Dual-Channel Competition

Jingjie Su[a], Kay-Yut Chen[a], Diana Yan Wu[b]

[a]College of Business, The University of Texas at Arlington

[b]Lucas College and Graduate School of Business, The San José State University

3.1 Introduction

Due to the advent of the online channel and ongoing digitalization, many firms have initiated multi-channel strategies, which is the combination of the vertical selling channel and direct selling channel (Verhoef et al., 2015). According to a survey from the article from Tedeschi (2000) in New York Times, a majority of traditional suppliers have expanded their business to the direct selling channel to the end market. The benefit of adapting the multi-channel selling strategy is that the supplier can generate more profit, but the downside is that it also stimulates the competition in selling quantity between the supplier and downstream retailer. In this type of supply chain, referred to as an omni-channel supply chain, the supplier and the retailer are not only partners but also competitors.

When developing the omni-channel strategy while mitigating the competition with the retailer, depending on the corporate objectives, the upstream suppliers can choose to distribute their products into one of the three possible channels: vertical sells, which only sell to the downstream retailer, dual sells, which sell to both the retailer and direct to the market, or direct sells, which only sell directly to the market. The supplier can also compete with the retailer in market price, selling quantity, product quantity, or product availability (Bell et al., 2002; K. Cattani et al., 2006; Chiang et al., 2003; Tsay & Agrawal, 2004a). The availability of these mitigation strategies for the supplier only when the supplier has the market power, which is the relative ability to manipulate the price of a good or service in the marketplace by controlling the level of supply, demand, or both (Frank, 2008). If the retailer has the market power, he also can use it as a competitor tool and against the supplier. Hence, who has the market power could be one of the important aspects in the dual channel supply chain.

Along this line of thought, we design the study to explore the potential effect of the market power. In the model, we consider a one-period complete information dual channel supply chain, in which consists of a supplier and a retailer. The supplier, who has no capacity constraint, sells the product to the retailer and also sells directly to the market via her private channel. The retailer can decide whether to invest in supplier production, retailer market, or product quality. Investing in a self or partner company is fairly common in business. Companies invest in certain projects to gain benefit. However, when the competitor is also acting as the upstream partner, whether to invest and how to invest becomes a complicated problem. In the model, we also allow both the supplier and the retailer to set the wholesale price, but only one wholesale price will be automatically selected by the supply chain system. The market power in the model refers to the high probability that a wholesale price will be selected. We investigate whether the interaction in responses changes when a supplier or a retailer has the market power. Given the complexity of the strategic interactions in a dual channel supply chain, and the multiple decisions in the model, the goals of the paper are simple: (1) whether the power changes the decisions? (2) Given the possible strategic interactions and noisy decision-making behaviors in the experiments, how does market power affect the supplier and the retailer?

To address these two research questions, we employ a combination of game theory analyses, human-subject experiments, behavioral economics modeling, and numerical analyses. Game theory analyses provide a base guideline for the predictions. However, decision makers normally deviate from optimal decisions (Donohue et al., 2018). Thus, conducting human-subject experiments is the most promising approach to examine the actual decisions.

We find that the retailer responds significantly to different levels of market power when making the investment decision as opposed to theory prediction, which is the market power has no effect on the investment decision. We also find that the supplier randomly decides the wholesale price as opposed to maximize her expected profit. It is difficult for the standard statistical analyses to explain the results because of the decision noise. Therefore, we develop a structural model incorporating bounded rational based on the quantal response equilibrium (QRE) framework (McKelvey & Palfrey, 1995) to capture and measure the strategic responses of the supplier and the retailer while controlling the decision bias.

Relying on numerical analyses, we characterize how the investment decision changes with different levels of bounded rationality. Our results reveal that as the bounded rationality of the supplier and the retailer increases, they are closer to making optimal decisions as theory predicted.

The rest of the paper is structured as follows. Section 3.2 summarized the related theoretical and behavioral literature in omni-channel management, market power in general competition of supplier-retailer systems, and supply chain coordination in the behavioral operations management. The model set up and theoretical prediction are detailed in Section 3.3. Section 3.4 describes the experimental design, protocol, and research hypotheses. Section 3.5 summarizes statistical results and observation findings. Behavioral models and implications are listed in Section 3.6. 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 Section 3.7.

3.2 Literature Review

This paper is the first to model market power in a dual channel Cournot quantity competition setting with a linear price function, and conduct human-subject experiments to investigate the supplier-retailer interactions. In addition, we integrate a variety of investment choices to the model to determine the optimal operational decisions of the supplier and the retailer. The relevant literature can be divided into three streams: omni-channel management, market power in general competition of supplier-retailer systems, and supply chain coordination in the behavioral operations management.

The first stream of literature relates to omni-channel management. There is an increasing number of firms have adapted omni-channel strategy (i.e. online or direct sales) as their preferred selling strategy in nowadays business (Tedeschi, 2000). When developing the omni-channel strategy, depending on the corporate objectives, the upstream suppliers can choose to distribute their products into one of the three possible channels: vertical sells, dual sells, or direct sells. There is also a growing literature on omni-channel management (K. D. Cattani et al., 2004; Tsay & Agrawal, 2004b). Most papers in this area study competition in price or selling quantity (Bell et al., 2002; K. Cattani et al., 2006; Chiang et al., 2003; Tsay & Agrawal, 2004a). Tsay and Agrawal (2000) examine the drivers of the strategies set by the suppliers and the retailers under a price-based competition and find that the structure of wholesale pricing mechanisms is able to coordinate the system but only under very limited conditions. Ha and Tong (2008) investigate the contracting and information sharing in dual channel supply chains under sells quantity competition and highlight the importance of contract type as a main driver under supply chain competition. Y. Lee et al. (2003) study the channel conflict of retailers, which is the competition that comes from the direct channel sales of the supplier. They provide suggestions for the managers in the retailing company to cope with channel conflict. Kim and Chun (2018) study the optimal strategy that retailers should use when facing the competition from the direct channel sales supplier.

We add to the literature by investigating how a variety of investment choices by the retailer can affect the dual channel competition and coordination. Specifically, the retailer has an opportunity to decide whether to make an investment in the production of the supplier (Hu et al., 2019), the retailer marketing (Ma et al., 2013), or the total product quality (Battigalli et al., 2007). Our model closely relates to two papers. First, Li and Lin (2006) have proved the evidence of the investment from retailers to suppliers. In this empirical study, they find that if the retailer invests in the supplier, he will have a better relationship with the supplier compared with no investment, and the supply chain coordination increases significantly. Second, Xie et al. (2011) study how product quality investment can affect the supply chain coordination in three different settings, including vertical integration, supplier Stackelberg, and retailer Stackelberg. In our model, we allow the retailer to make an investment in supplier production, retailer market, or product quality. Hence, we can examine how the supplier and the retailer respond to change reflecting the investments.

The second stream of literature relates to market power in the supply chain system. In economics, market power is a relative ability of firms to manipulate the price of a good or service in the marketplace by controlling the level of supply, demand, or both (Frank, 2008). It is also known as bargaining power. D. Wu et al. (2009) model the bargaining power between retailer and supplier in different supply chain settings. They model the wholesale price as the function of barging power and find the unique Nash equilibrium only exists in the vertical integrated supply chain set up. In Y.-J. Chen et al. (2012), they developed a model to capture how a retailer should perform the procurement and react to high or low bargaining power. They find the dependence of the procurement decision on the bargaining power.

Because we allow both the supplier and the retailer to set the wholesale price simultaneously in our model, and only one wholesale price will be randomly selected by the supply chain system. Hence, we define the market power as the high probability of a wholesale price being selected. For example, if the retailer has the market power, the probability of selecting his wholesale price is higher than the probability of selecting the supplier wholesale price. In the game-theoretic setting, our model predicts that the market power has no effect on the investment decision of the retailer in the dual channel setting. Varying the market power between the supplier and the retailer, we investigate how the market power actually affects the decisions in the experiments.

The last stream of literature relates to the experimental findings in behavioral operations management. As early as Chamberlin (1948) and Smith (1962), researchers have been using human-subjects experiments to understand the behavioral factors affecting decisions. There has been growing interest in the behavioral operations management after Schweitzer and Cachon (2000) experimental paper which reveals most of the common decision biases, such as risk/loss aversion, perspective theory, and waste/stockout aversion, in the newsvendor problem. Haitao Cui et al. (2007) incorporate the fairness concerns in a conventional dyadic channel to investigate how the supplier and the retailer coordination may be affected by the fairness. Bolton and Ockenfels (2000) demonstrate that individuals are motivated by both the payoff they received and the payoff of others in the system and show that reciprocity plays an important role in certain settings.

Standard operations management models follow economic assumptions that assume humans are fully rational, and they will always make the decisions to maximize their expected profit. According to Donohue et al. (2018), decision makers normally violate this assumption either because they are bounded rational (i.e. fail to maximize the expected profit because of the error or lack of resource (Su, 2008)), or because they have different utility functions (i.e. in addition to the expected profit, other attributes are included in the profit calculation (Katok & Wu, 2009)). Two main observations from our experiments. First, the human subjects in our experiments were responding to the market power as opposed not to. Second, subjects' interactions were corresponding to the changing in production cost and market demand also significantly impacted as opposed to the investment decisions. Adopting the quantal response equilibrium (QRE) framework, our behavioral model structurally shows that bounded rationality seems to be one of the main drivers that impact the supplier and the retailer interactions in the dual channel supply chain.

We believe that our study is unique in integrating operations management considerations into the study of the market power and investment decisions from a behavioral standard point. To the best of our knowledge, we are the first to investigate the strategic interactions of the supplier and the retailer, including investment, wholesale, and investment tolerance, in a complete information dual channel setting. Through a behavioral lens, we believe that our results offer novel insights that help in understanding the importance of the market power and investment in the supplier-retailer setting for practitioners.

3.3 Model Setting and Game Theoretical Prediction

We consider a one-period model in a dual channel supply chain, in which consists of a supplier (she) and a retailer (he), with complete information setting. The retailer buys a product from the supplier at a wholesale price (w) and sells the product to the market at a market price (p). When selling to the market, the retailer pays a per unit selling cost (c_r). The supplier, who has no capacity constraint, sells the product to the retailer at a per unit production cost (c), and also sells directly to the market via her private channel at the market price. When directly selling to the market, the supplier pays a per unit selling cost (c_s). The market is modeled as a Cournot quantity competition with a downward linear price function, given by: $p(q_s, q_r) = \delta - \beta(q_s + q_r)$, where δ is the maximum market demand, β is the sensitivity of the price to the total selling quantities, and $(q_s + q_r)$ are the selling quantities set by the supplier and the retailer respectively.

The retailer can decide whether to invest in one of the three projects at an investment cost (I): (1) invest in the supplier production, it can reduce the supplier per unit production cost from c to c_i. (2) Invest in the retailer marketing cost, it can reduce the retailer per unit selling cost from c_r to 0. (3) Invest in the total quality of the product, it can increase the maximum market demand from δ to $(\delta + \delta_i)$. The retailer can also decide not to invest in either of the projects.

We also incorporate the market power (α), defined as the probability of whose wholesale price will be selected, into the model. In our model, we allow both the supplier and the retailer to set their own desirable wholesale prices simultaneously, but only one wholesale price, either chosen from the supplier or the retailer, will be automatically selected by the supply chain system. For example, if the retailer has the market power, the probability of selecting his wholesale price (w_r), which is favorable to him, by the supply chain system, is higher than the probability of selecting the supplier wholesale price (w_s).

The following table summarizes the sequences of the game.

Table 3.1: Game Sequence

Stage 1	Retailer decides whether to invest in a project.
Stage 2	Supplier sets a wholesale price; simultaneously, retailer sets a wholesale price.
Stage 3	Supply chain system automatically selects a wholesale price; profit of each player is realized.

The profit of the supplier and the retailer of each investment project, including not invest, are listed below.

(1) Invest in supplier production:

$$\pi_{r|1} = \alpha((p - w_r - c_r)q_r - I) + (1-\alpha)((p - w_s - c_r)q_r - I)$$
$$\pi_{s|1} = \alpha((p - c_i - c_s)q_s + (w_r - c_i)q_r) + (1-\alpha)((p - c_i - c_s)q_s + (w_s - c_i)q_r) \tag{3.1}$$

(2) Invest in retailer marketing cost:

$$\pi_{r|2} = \alpha((p - w_r)q_r - I) + (1-\alpha)((p - w_s)q_r - I)$$
$$\pi_{s|2} = \alpha((p - c - c_s)q_s + (w_r - c)q_r) + (1-\alpha)((p - c - c_s)q_s + (w_s - c)q_r) \tag{3.2}$$

(3) Invest in total quality:

$$\pi_{r|3} = \alpha((p_i - w_r - c_r)q_r - I) + (1-\alpha)((p_i - w_s - c_r)q_r - I)$$
$$\pi_{s|3} = \alpha((p_i - c - c_s)q_s + (w_r - c)q_r) + (1-\alpha)((p_i - c - c_s)q_s + (w_s - c)q_r) \tag{3.3}$$

(4) No investment:

$$\pi_r = \alpha((p - w_r - c_r)q_r) + (1-\alpha)((p - w_s - c_r)q_r)$$
$$\pi_s = \alpha((p - c - c_s)q_s + (w_r - c_i)q_r) + (1-\alpha)((p - c - c_s)q_s + (w_s - c_i)q_r) \tag{3.4}$$

where $p(q_s, q_r) = \delta - \beta(q_s + q_r)$ and $p_i(q_s, q_r) = \delta + \delta_i - \beta(q_s + q_r)$.

3.3.1 Best Response and Numerical Analysis

Because of the optimal investment decision for the retailer is depending on eight exogenous parameters (i.e. the market power, supplier production cost, reduction in production cost, supplier directly selling cost, retailer marketing cost, maximum market demand, increasing in market demand, and sensitively of the market price), there are obviously infinite sets of parameters. Hence, we calculate the best response of the retailer profit, and arbitrarily pick two parametric settings, where the incentives are representative and relatively close to the real business environment, to illustrate how the market power or the changing in supplier production cost and the maximum market demand can affect the investment decision of the retailer. The best-response of the retailer profit, given different investment choices, are listed below. Please see Appendix A for the proof.

(1) Invest in supplier production:

$$\pi_{r|1} = \alpha\left(\frac{(\delta - c_i + c_s - 2c_r)^2}{9\beta}\right) + (1-\alpha)\left(\frac{4(c_s - c_r)^2}{25\beta}\right) - I \tag{3.5}$$

(2) Invest in retailer marketing cost:

$$\pi_{r|2} = \alpha \left(\frac{(\delta - c + c_s)^2}{9\beta} \right) + (1 - \alpha) \left(\frac{4(c_s)^2}{25\beta} \right) - I \tag{3.6}$$

(3) Invest in total quality:

$$\pi_{r|3} = \alpha \left(\frac{(\delta + \delta_i - c + c_s - 2c_r)^2}{9\beta} \right) + (1 - \alpha) \left(\frac{4(c_s - c_r)^2}{25\beta} \right) - I \tag{3.7}$$

(4) No investment:

$$\pi_r = \alpha \left(\frac{(\delta - c + c_s - 2c_r)^2}{9\beta} \right) + (1 - \alpha) \left(\frac{4(c_s - c_r)^2}{25\beta} \right) \tag{3.8}$$

For the numerical illustration, we pick $c = 40$,$c_s = 10$,$c_r = 4$,$\delta = 100$ and $\beta = 0.5$ as basic variables, two levels of the market power $\alpha = 90\%$ and $\alpha = 10\%$, two levels of the decreasing in supplier production cost $c_i = 25$ and $c_i = 32$, and two levels of the increasing in demand $\delta_i = 8$ and $\delta_i = 15$, again somewhat arbitrarily but with enough separation so that the incentives are clear.

The numerical illustration is designed to track and explain the changing market power or supplier production cost and maximum market demand may change the retailer investment decision, all else equal. We plot retailer expected profit as a function of two parameter changes as shown in Figure 3.1.

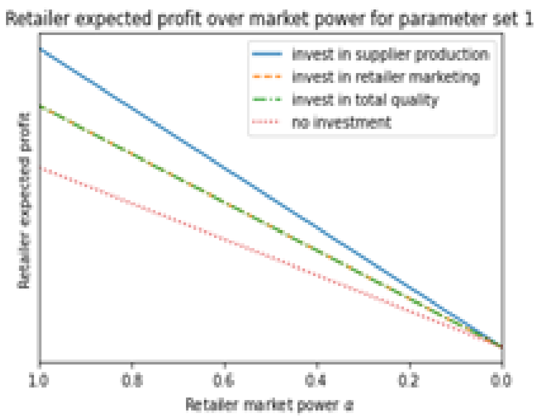
3.3.1.1 Market Power

Theory predicts that when investing in supplier production under parameter set 1, the retailer always earns the highest expected profit. Under parameter set 2, the retailer always earns the highest expected profit when investing in total quality. This result indicates when changing the investment decision, the retailer should only respond to the changing of parameter set, but not the changing of market power.

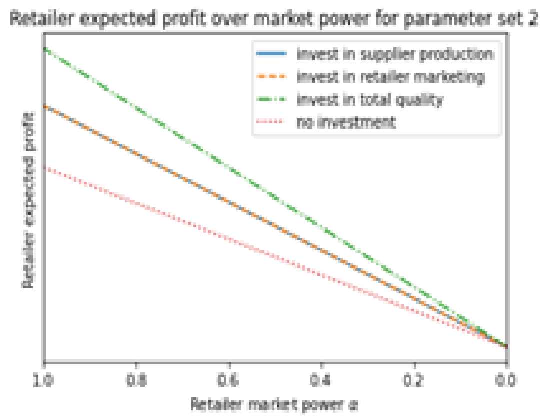
3.3.1.2 Supplier Production Cost & Maximum Market Demand

Theory predicts that as the supplier production cost (the maximum market demand increases, respectively), the optimal investment decision for the retailer changes from investing in production to investing in total quality (from investing in total quantity to investing in retailer marketing, respectively). This result indicates that the optimal decision of the retailer changes with changing of parametric settings with certain thresholds.

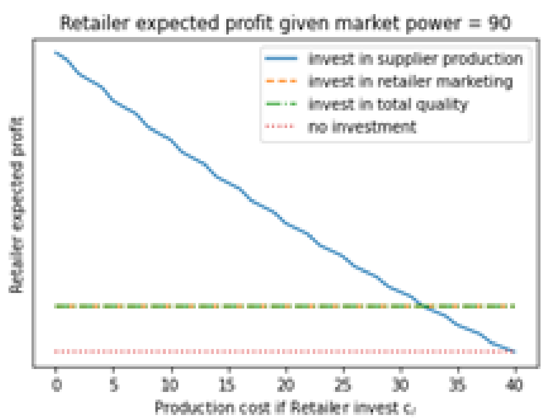
Figure 3.1: Retailer Expected Profit to the Changing of Parameters



(a) Retailer Expected Profit over market power for parameter set 1



(b) Retailer Expected Profit over market power for parameter set 2



(c) Retailer Expected Profit given market power = 90

(d) Retailer Expected Profit given market power = 10

3.4 Experimental Study

We conduct a series of human-subject experiments to investigate if and how different levels of the market power or costs can affect the decisions of the supplier and the retailer.

3.4.1 Setting Calibration

The model setting is characterized by eight parameters (market power α, supplier production cost c, reduction in production cost c_i, supplier directly selling cost c_s, retailer marketing cost c_r, maximum market demand δ, increase in market demand δ_i, and sensitivity of market price β). In a traditional test-the-theory study, the design would test multiple sets of parameters and see if theoretical prediction changes along with behavior responds.

There are obviously infinite sets of parameters that we can compare and test. However, the main goal of this paper is to study how different levels of market power or costs can affect the decisions of the supplier and the retailer. Hence, the design of the experiments focuses on two key variables, the market power, and combination of supplier production cost and market demand. We pick the same parametric settings as in Section 3.3.1 to examine how the supplier and the retailer actually respond to the changes in the experiments.

Table 3.2 summarizes our parameter settings.

Table 3.2: Calibration of Experimental Parameters

Parameters	Value in Experiment
α: market power	90% or 10%
c: supplier production cost	40
c_i: reduction in production cost	25 or 32
c_s: supplier marketing cost	4
δ: maximum market demand	100
δ_i: increase in market demand	8 or 15
β: sensitivity of market price	0.5

3.4.2 Experimental Design

We use a standard 2×2 between-subjects full factorial design for a total of four treatments. Table 3.3 summarizes the experiment design and expected profit for the supplier and the retailer.

Table 3.3: Experimental Design

		90 Para 1	10 Para 1	90 Para 2	10 Para 2
w_r^*	No investment	40	40	40	40
	Invest in production	25	25	32	32
	Invest in marketing	40	40	40	40
	Invest in quality	40	40	40	40
w_s^*	No investment	67.4	67.4	67.4	67.4
	Invest in production	59.9	59.9	59.9	59.9
	Invest in marketing	69	69	69	69
	Invest in quality	71.4	71.4	74.9	74.9
Retailer expected profit, given investment cost = 0	No investment	1376	696	1376	696
	Invest in production	1794	742	1574	718
	Invest in marketing	1576	737	1576	737
	Invest in quality	1574	718	1794	742
Retailer maximum profit, given investment cost = 0	No investment	1461	1461	1461	1461
	Invest in production	1926	1926	1681	1681
	Invest in marketing	1681	1681	1681	1681
	Invest in quality	1681	1681	1926	1926
Supplier expected profit	No investment	518	1182	518	1182
	Invest in production	915	1993	705	1587
	Invest in marketing	445	1196	445	1196
	Invest in quality	705	1587	915	1993

Table 3.4: Experimental Design-continued

		90 Para 1	10 Para 1	90 Para 2	10 Para 2
Supplier maximum profit	No investment	1265	1265	1265	1265
	Invest in production	2128	2128	1697	1697
	Invest in marketing	1290	1290	1290	1290
	Invest in quality	1697	1697	2128	2128

3.4.3 Research Hypotheses

Based on the parametric settings we picked in section 3.4.1, we calculate the supplier and the retailer expected profit assuming the investment cost is equal to zero (Table 3.3). The first hypothesis follows directly from the quantitative predictions of the model.

HYPOTHESIS 1 (Investment Decision).

HYPOTHESIS 1a The retailer should always invest in the production of supplier in both 90 Para 1 and 10 Para 1 treatments.

HYPOTHESIS 1b The retailer should always invest in quality in both 90 Para 2 and 10 Para 2 treatments.

Even if the data deviate from these precise predictions, the model can still make useful qualitative predictions. The main point summarized in section 3.3.1 is that the optimal investment decision retailer is a threshold strategy. Hence, the investment decision will only be affected by the main trade-off of the model, but not by the market power. Our second hypothesis reflects this qualitative prediction.

Hypothesis 2 (Investment Response).

HYPOTHESIS 2a Investment decision of the retailer is not affected by market power.

HYPOTHESIS 2b Investment decision of the retailer is affected by the changing production cost and market demand.

Comparing across different investment options, we can find the investment threshold for each project. When the threshold is higher than the investment cost, the retailer should always choose not to make an investment, which leads us to our third hypothesis.

HYPOTHESIS 3 (Investment Threshold). When choosing an investment project, the retailer always sets the investment tolerance level at the threshold.

We intentionally pick the parametric settings that optimal decisions of the wholesale price and the maximum profit of the supplier or the retailer are the same in different levels of the market power treatments. If the optimal wholesale price in different levels of market power treatments are the same, we should not observe any different actual performance.

HYPOTHESIS 4 (Wholesale Prices).

HYPOTHESIS 4a The retailer will set the wholesale price equal to the supplier production cost.

HYPOTHESIS 4b The wholesale price decision of the supplier will not be affected by the changing of the market power.

3.4.4 Experimental Procedures

We followed the standard experimental economics procedures and used no deception. The experiments were conducted on Amazon Mechanical Turk (MTurk) via Software Platform for Human Interaction Experiments (SoPHIE) (https://www.sophielabs.com).

Multiple studies have shown that MTurk is a preferred channel to collect experimental data because of its flexibility. According to Y. S. Lee et al. (2018), although some minor variations exist between supply chain experiments conducted on MTurk and in the local laboratory, most of the main conclusions are consistent.

In each of the experiments, in order to ensure the participants are understanding the game, they are required to read the instruction and to take the quiz. After passing the quiz question, participants play two practice rounds as the role of the Supplier and the Retailer. Then they will be randomly assigned a role, either the Supplier or the Retailer, and pair with another participant to play the real game for one round. During the game, while choosing the investment project, the Retailer is also asked to input an investment cost tolerance threshold. The Retailer is being told that the investment cost is uniformly distributed between [0,600] and the computer will randomly generate an investment cost from the distribution. If this randomly generated investment cost is lower than the tolerance threshold set up by the Retailer, the computer will decide the investment is successful and hence the Retailer or the Supplier will get the resulting benefit, such as reduction of product cost or marketing cost, from the corresponding investment option. If the randomly generated investment cost is higher than the tolerance threshold set up by the Retailer, the computer will decide the investment is failed and the Retailer and Supplier will end up in the situation with no investment option.

The following table summarizes the sequences of the experiment.

Similar to other economic experiments, incentives are controlled by monetary payoffs. Participants receive game rewards based on their performance from the resulting profit, plus a small amount of the show-up fee. A total of 362 U.S. MTurk participants, who have completed at least 100 tasks with at least 95% approval rate, finished the experiment. The average payment was $1.1, which is in-line with the earning rates on MTurk for a 15-minutes task. Please refer to Appendix B for experiment screenshots.

Table 3.5: Experiment Sequence

Stage 1	Retailer decides whether to invest in a project, and also decides the investment threshold.
Stage 2	The computer will randomly generate an investment cost and compare it with the input of Retailer investment threshold to decide if the investment is successful. The realized investment project and investment cost will be shown to both Retailer and Supplier in Stage 3.
Stage 3	Supplier sets a wholesale price; simultaneously, Retailer sets a wholesale price.
Stage 4	Supply chain system automatically selects a wholesale price, and optimal ordering quantities for the Supplier and the Retailer. Then the computer displays profit for each player.

3.5 Experimental Result

In this section, we analyze the experimental data with respect to the hypotheses established in section 3.4 and present the findings accordingly. Table 3.6 summarizes theoretic predictions and decisions outcomes under each treatment condition.

Table 3.6: Summary Statistics

Investment Decision	Prediction	90 Para 1 N = 39	10 Para 1 N = 47	90 Para 2 N = 43	10 Para 2 N = 52
No investment	-	7.69%	12.77%	2.33%	3.85%
Invest in production	100 % for Para 1	53.85%	42.55%	20.93%	42.32%
Invest in marketing	-	30.77%	36.17%	18.6%	42.31%
Invest in quality	100 % for Para 2	7.69%	8.51%	58.14%	11.54%

Investment Tolerance	Prediction	90 Para 1 N = 39	10 Para 1 N = 47	90 Para 2 N = 43	10 Para 2 N = 52
No investment	-	-	-	-	-
Invest in production	418 & 46 for Para 1 192 & 22 for Para 2	236	231	160	204
Invest in marketing	200 & 41 for Para 1 200 & 41 for Para 2	243	152	178	288
Invest in quality	198 & 22 for Para 1 418 & 46 for Para 2	150	206	274	238

Table 3.7: Summary Statistics-continued

Retailer Wholesale Price		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	40	48	58	52	65
Invest in production	25 for Para 1 32 for Para 2	50	55	43	60
Invest in marketing	40	54	62	70	61
Invest in quality	40	40	53	53	73

Supplier Wholesale Price		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	67.4	64	70	65	45
Invest in production	60 for Para 1 63 for Para 2	61	55	59	65
Invest in marketing	69	61	57	63	68
Invest in quality	71 for Para 1 75 for Para 2	40	64	68	60

3.5.1 Result 1: Retailers did not always make the optimal investment decisions.

Table 3.8 displays the predicted and the actual percentage of each investment decision for the retailer by different treatments. Theory predicts the optimal decision for the retailer is to invest in supplier production in both 90 Para 1 and 10 Para 1 treatments, and to invest in total quality in both 90 Para 2 and 10 Para 2 treatments.

The observed investment decisions show that the retailer invested in supplier production

53.85% in 90 Para 1 treatment and 42.55% in 10 Para 1 treatment, and they invested in total quality 58.14% in 90 Para 2 treatment and 11.54% in 10 Para 2 treatment. Results are significantly less than prediction (one-sample Wilcoxon test with p-value < 0.01) in all four treatments. Also, the distribution of the investment decision is also significantly lower than prediction (Fisher's Exact test with p-value < 0.01). This observation shows that the retailers did not follow theory predictions to invest in supplier production or in total quality. Hence, Hypothesis 1A and 1B are rejected.

Table 3.8: Investment Decision Outcomes

Investment Decision		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	-	7.69%	12.77%	2.33%	3.85%
Invest in production	100 % for Para 1	53.85%	42.55%	20.93%	42.32%
Invest in marketing	-	30.77%	36.17%	18.6%	42.31%
Invest in quality	100 % for Para 2	7.69%	8.51%	58.14%	11.54%

3.5.2 Result 2: Investment decisions are affected by the change of production cost and market demand but partially affected by the market power.

Theory prediction that the investment decision of the retailer should not be affected by the changing of market power. We first compare the investment decisions in 90 Para 1 treatment and 10 Para 1 treatment using the Fisher's Exact test. Results show that the retailers' investment decisions were not significantly (p-value = 0.747) affected by changing market power in Para 1 treatments. Next, we compare the investment decisions in 90 Para 2 treatment and 10 Para 2 treatment. Results show that the retailers' investment decisions were significantly (p-value < 0.01) affected by changing market power in Para 2 treatments. This indicates that, in some market power situations, the retailers make significantly different investment decisions. Hence, Hypothesis 1B is partially supported. This is the second evidence that the retailers did not follow the theory prediction.

We combine 90 Para 1 treatment with 10 Para 1 treatment, and 90 Para 2 treatment with 10 Para 2 treatment to investigate whether the investment decision switches from investing in supplier production to investing in quality when the retailers have cost of supplier production and the market demand is changing. Results show that the retailers make significant (Fisher's exact test, p-value < 0.01) different investment decisions between Para 1 and Para 2 treatments. Hence, Hypothesis 2B is supported.

3.5.3 Result 3: Investment cost tolerance is affected by the market power and the changing of production cost and market demand.

In the experiments, when making the investment decision, the retailers also decide their investment tolerance level. If the randomly generated investment cost is higher than their tolerance level, they make no investment. Theory predicts that the best response tolerance level should be the difference between the expected profit of an investment decision of the retailer and the expected profit if the retailer chooses not to invest. Table 8 displays the predicted and the actual average investment tolerance level for each treatment.

Aside from direct theoretical comparison, we calculate the tolerance difference between the retailers' actual investment tolerance decision and the tolerance best response (e.g. $Tolerance_{diff} = Tolerance_{actual} - Tolerance_{best}$). The two sample Mann-Whitey U test shows that the tolerance difference in each treatment is significantly (p-value < 0.05) differ-

Table 3.9: Investment Tolerance Outcomes

Investment Tolerance		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	-	-	-	-	-
Invest in production	418 & 46 for Para 1 192 & 22 for Para 2	236	231	160	204
Invest in marketing	200 & 41 for Para 1 200 & 41 for Para 2	243	152	178	288
Invest in quality	198 & 22 for Para 1 418 & 46 for Para 2	150	206	274	238

ent from zero. This result indicates that the retailers did not set the investment tolerance level at the threshold in all four treatments. Hence, Hypothesis 3 is rejected.

Next, we investigate whether the investment tolerance levels set by the retailers are too high or too low compared with the threshold. We found that in both 90 Para 1 treatment and 90 Para 2 treatment, the tolerance different is significantly (Mann-Whitney test, p-value < 0.05) lower than zero, and in both 10 Para 1 treatment and 10 Para 2 treatment, the tolerance different is significantly (Mann-Whitney test, p-value < 0.01) higher than zero. This indicates that when the retailers have a high market power (i.e. 90%), they tend to set a lower tolerance of investment cost compared with the theory. Conversely, when the retailers have a low market power (i.e. 10%), they tend to set a higher tolerance limit for investment cost than the theory prediction.

We also investigate whether the investment tolerance levels are affected by different levels of the market power. We run the regression as the tolerance difference is the dependent variable and the market power is the treatment dummy, where 1 indicates the retailers have a high market power and 0 indicates the suppliers have a high market power. Results in Table 3.10 show that the coefficient of market power is negative and significant with a p-value less than 0.01. This indicates the market power has a negative impact on the investment tolerance decision. It also shows that if the retailers have less market power in the supply chain, they tend to set a higher tolerance level.

Table 3.10: Regression Analysis

	Para 1	Para 2
Power dummy	-222.8276 (0.000)	-299.8129 (0.000)

3.5.4 Result 4: Retailers' wholesale prices are different from prediction; suppliers' wholesale prices are partially different from prediction.

According to theory, the retailers should always set the wholesale price equal to the suppliers' production cost. We calculate the wholesale price difference between the retailers' actual decision and the best response (e.g. $w_r(diff) = w_r(actual) - w_r(best)$). The two sample Mann-Whitey U test shows that the wholesale price difference set by the retailer in each treatment is significantly (p-value < 0.01) different from zero. This indicates that when setting the wholesale price, the retailers significantly deviate from the prediction. Hence, Hypothesis 4A is rejected.

Table 3.11: Retailer Wholesale Price Outcome

Retailer Wholesale Price		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	40	48	58	52	65
Invest in production	25 for Para 1 32 for Para 2	50	55	43	60
Invest in marketing	40	54	62	70	61
Invest in quality	40	40	53	53	73

The wholesale price difference set by the supplier in each treatment is significantly (p-value < 0.01) different from zero in three out of four treatments. This indicates that when setting the wholesale price, the suppliers partially deviate from the prediction. Comparing the supplier wholesale prices across different levels of market power, we find that when making the wholesale price decisions, the suppliers were not affected by the market power

Table 3.12: Supplier Wholesale Price Outcome

Supplier Wholesale Price		90 Para 1	10 Para 1	90 Para 2	10 Para 2
	Prediction	N = 39	N = 47	N = 43	N = 52
No investment	67.4	64	70	65	45
Invest in production	59.9 for Para 1 63.4 for Para 2	61	55	59	65
Invest in marketing	69	61	57	63	68
Invest in quality	71.4 for Para 1 74.9 for Para 2	40	64	68	60

(two-sample Wilcoxon test with p-value > 0.6). Hence, Hypothesis 4B is supported.

Thus far we have identified that the decisions of the suppliers and the retailers were significantly deviated from theory prediction in most cases. Specifically, the rate of investment in supplier production in the Para 1 treatments and the rate of investment in total quality in the Para 2 treatments were significantly (all p-value < 0.01) lower than 100% by $42\% - 88\%$. The observed wholesale prices set by either the supplier or the retailer were also significantly (p-value < 0.01) different from predictions. The observations suggest that the suppliers' and the retailers' behaviors are deviated from predictions.

Prior behavioral operations management literature has shown that game theory does not provide a precise prediction for decision makers (Donohue et al., 2018). When making a decision, individuals sometimes experience bounded rationality, which prevents them from making the optimal decision (Su, 2008). Other times, individuals may have additional utility, such as social preference, in addition to the profit realization when maximizing their expected profit (Katok & Wu, 2009).

In our experiments, participants seem to be bounded rationality when making their decisions.

3.6 Behavioral Model and Estimation

We have consistently observed the retailers do not make the optimal investment decision (Result 1 & 2). The retailers' decisions were affected by the switching of market power, cost of production, and changing of market demand. However, the basic statistical analysis cannot fully capture the strategic interactions between the supplier and the retailer (Result 4). Hence, a structured behavioral model is needed to capture and measure the rationality in order to explain the decision biases.

To construct the behavioral model, we have an assumption which is motivated by the statistical results, which is that decisions of the suppliers and the retailers seem noisy, and likely to be explained by the bounded rationality. To control the decision noise, we employ the quantal response equilibrium (QRE) framework (McKelvey & Palfrey, 1995), which is supported by the quantal choice theory (Luce, 2012), to the behavioral model.

There are other possible behavioral explanations for the observed statistical results, such as loss aversion, fairness concerns, and reciprocity. We believe in this paper bounded rationality alone is a dominant factor and is sufficient to explain the major empirical results.

3.6.1 The Quantal Response Equilibrium (QRE)

We construct the behavioral model with the quantal response equilibrium (QRE) framework (Su, 2008) by backward induction. Because the investment decision and the investment cost tolerance decision are made in the same stage by the retailer, we use one decision parameter to measure the behavior. Hence, the model includes a total of three decision parameters. We use x for decision variables, and u for utility functions, with w_r,w_s and i to index the retailer wholesale price, the supplier wholesale price, and the investment and cost tolerance. We use γ for bounded rationality parameters, and assume γ can be different for different decisions (D. Y. Wu & Chen, 2014), let γ_{wr},γ_{ws} and γ_i to be the bounded rationality parameters for the wholesale price decision of retailer, the wholesale price decision of supplier, and the investment and cost tolerance decision respectively. Follow to prior behavioral operations management literature, we also assume all participant are homogeneous (Y. Chen et al., 2012)

Table 3.13: QRE Parameter Summary

	Decision	Bounded Rationality
Investment decision and the investment cost tolerance	i	γ_i
Retailer wholesale price	w_r	γ_{wr}
Supplier wholesale price	w_s	γ_{ws}

3.6.1.1 Wholesale Price of Supplier and Retailer

We start with the last stage of the game where the supplier and the retailer simultaneously make their wholesale price decisions. The utilities for the supplier and the retailer, conditioned on the investment decision and the investment cost tolerance, for the wholesale price decisions are given by:

$$u_s(x_{ws}, x_{wr}, x_i) = \alpha((p-c-c_s)q_s + (x_{wr}-c)q_r) + (1-\alpha)((p-c-c_s)q_s + (x_{ws}-c)q_r)$$

$$u_r(x_{ws}, x_{wr}, x_i) = \alpha((p-x_{wr}-c_r)q_r) + (1-\alpha)((p-x_{ws}-c_r)q_r) \tag{3.9}$$

where $p(q_s, q_r) = \delta - \beta(q_s + q_r)$, δ is the maximum market demand, β is the sensitivity of the price, q_s and q_r are the selling quantity, and α represents when the retailer has the market power.

Since the sale quantity decisions of the supplier and retailer are automatically calculated by the computer using the best response function, and the supplier and the retailer are making the wholesale price decisions simultaneously, a pair of distributions $(P_{ws}(x_{ws}), P_{wr}(x_{wr}))$ can satisfy the quantal response equilibrium conditions.

$$P_{ws}(x_{ws}) = \frac{e^{\gamma_{ws} E_{ws}(u_s(x_{ws}, x_{wr}, x_i))}}{\sum_{ws'} e^{\gamma_{ws} E_{ws}(u_s(x'_{ws}, x_{wr}, x_i))}} \tag{3.10}$$

$$P_{wr}(x_{wr}) = \frac{e^{\gamma_{wr} E_{wr}(u_r(x_{wr}, x_{ws}, x_i))}}{\sum_{wr'} e^{\gamma_{wr} E_{wr}(u_r(x'_{wr}, x_{ws}, x_i))}} \tag{3.11}$$

where γ_{ws} and γ_{wr} are the bounded rationality parameters for the wholesale price decisions. Similar to D. Y. Wu and Chen (2014), when $\gamma_{ws} = 0$ or $\gamma_{wr} = 0$, the individual has no intelligence when deciding the wholesale price, hence (s)he randomly chooses his/her decision among all possible choices with equal probability. Conversely, when $\gamma_{ws} \to \infty$ or $\gamma_{wr} \to \infty$, the individual is fully rational and will choose the optimal choice.

The expected utilities of the supplier, over the retailer quantal response distribution, is given by:

$$E_{ws}(u_s(x_{ws}|x_{wr}, x_i)) = \sum_{ws} P_{ws}(x_{ws}) u_s(x_{ws}, x_{wr}) \tag{3.12}$$

The expected utilities of the retailer, over the supplier quantal response distribution, is given by:

$$E_{wr}(u_r(x_{wr}|x_{ws}, x_i)) = \sum_{wr} P_{wr}(x_{wr})u_r(x_{ws}, x_{wr}) \tag{3.13}$$

3.6.1.2 Investment Decision and Investment Cost Tolerance

By backward induction, we next analyze the investment and the investment cost tolerance decision of the retailer. Because the retailer simultaneously makes the investment decision and the investment cost tolerance decision. Given the wholesale price decisions of supplier and the retailer, the retailer quantal response probability of the investment and the investment cost tolerance, including all possible combination outcomes, is given by:

$$P_i(x_i) = \frac{e^{\gamma_i E_i(u_r(x_i, x_{ws}, x_{wr}))}}{\sum_{i'} e^{\gamma_i E_i(u_r(x_i', x_{ws}, x_{wr}))}} \tag{3.14}$$

where γ_i is the bounded rationality parameter for the investment and the investment cost tolerance decision of the retailer.

The expected utilities of the retailer, over the investment and investment cost tolerance quantal response distribution, is given by:

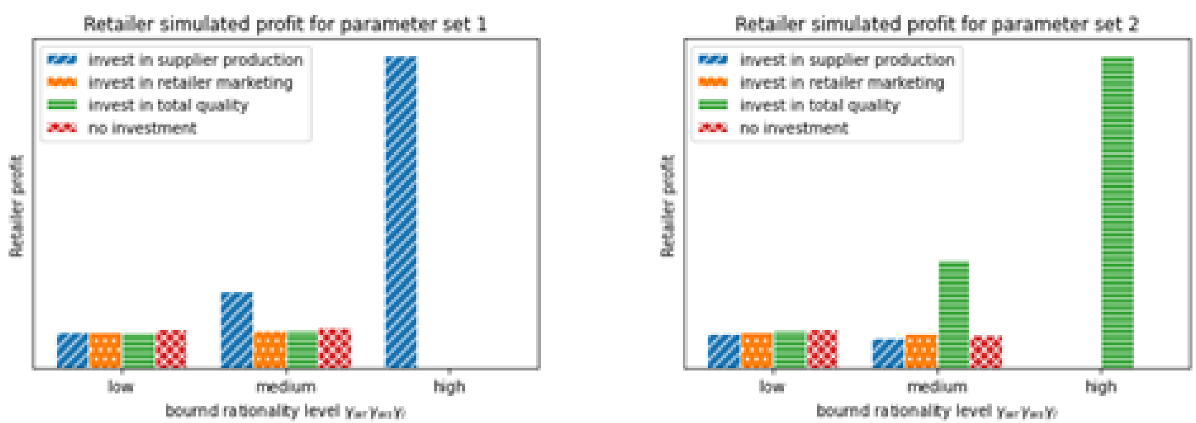
$$E_i(u_r(x_i|x_{ws}, x_{wr})) = \sum_{i} P_i(x_i)u_r(x_{ws}, x_{wr}) \tag{3.15}$$

3.6.2 Behavioral Model Implications

The behavioral model, incorporating bounded rationality, is designed to track strategic interactions of the supplier and the retailer and explain the main empirical result why the retailer investment decision significantly deviates from the prediction. In this section, we establish a clear picture of how the change of bounded rationality levels impacts the investment decisions, all else equal. Specifically, we use the parameters from the experiments, and run the model using a range of bounded rationalities (i.e. γ_{ws}, γ_{wr} and γ_i), which represent the three decisions (the supplier wholesale price, the retailer wholesale price). We plot the retailer expected profit as a function of the bounded rationalities as shown in Figure 3.2.

The model predicts that if both the supplier and the retailer have low bounded rationalities for their decisions, the retailer basically makes randomly choices between his four options, including invest in supplier production, invest in retailer marketing, invest in total quality, and no investment, in both parametric settings. As the bounded rationalities increase from low to high, the retailer will always choose to invest in supplier production under parametric setting 1, and always choose to invest in total quality under parametric setting 2. This result shows that bounded rationality has a strong impact on the investment decision of the retailer.

Figure 3.2: Retailer Expected Profit to the Changing of Bounded Rationalities



(a) Retailer Simulated Profit for Parameter Set 1 (b) Retailer Simulated Profit for Parameter Set 2

3.6.3 Model Estimation

We use the maximum log-likelihood to estimate the parameters of the behavioral model, given in Section 3.6.1. There are three bounded rationality parameters (γ_{ws}, γ_{wr} and γ_i), representing the three decisions (the supplier wholesale price, the retailer wholesale price, the combination of the investment decision and the investment cost tolerance). Since the decisions are assumed to be conditioned independent, the log-likelihood function is simply the sum of the log of the probability of each decision.

$$LL(\theta) = \sum (log(P_{ws}(x_{ws})) + log(P_{wr}(x_{wr})) + log(P_i(x_i))) \tag{3.16}$$

where $\theta = \gamma_{ws}, \gamma_{wr}, \gamma_i$ are the behavioral parameters, and the decisions $(x_{ws}, x_{wr} and x_i)$.

Table 3.14 summarizes the estimation results based on the maximum log-likelihood.

Table 3.14: Model Estimations

	90 Para 1	10 Para 1	90 Para 2	10 Para 2
Log-likelihood	525.90	643.86	558.26	713.55
γ_i:investment and investment cost tolerance bounded rationality	0.0105 (0.010)	0.0030 (0.225)	0.0095 (0.000)	0.0000 (1.000)
γ_{ws}:supplier wholesale price bounded rationality	0.0069 (0.301)	0.0000 (1.000)	0.0042 (0.425)	0.0000 (1.000)
γ_{wr}:retailer wholesale price bounded rationality	0.0023 (0.000)	0.0143 (0.000)	0.0028 (0.000)	0.0112 (0.003)

Note: p-value are in parentheses

3.6.3.1 Estimation Result 1: Retailers are bounded rationality when setting the wholesale price.

One of the main empirical conclusions of the paper is that the retailer sets a significantly higher wholesale price compared with the prediction.

Please see Table 3.14, we use the likelihood ratio test to check whether the parameter is significantly different from zero (no intelligence). The result shows that the bounded rationality parameters for the retailer wholesale price (γ_{wr}) are significantly different from zero (p-value < 0.01) in all four treatments. Hence, bounded rationality can explain this result.

3.6.3.2 Estimation Result 2: Suppliers have no intelligent when setting the wholesale price.

Estimation results show that the bounded rationality parameters of supplier wholesale price(γ_{ws}) are not significantly different from zero in all four treatments. The result indicates that when deciding the wholesale price, the suppliers were purely random. This is consistent with the observation results that in some treatments, the supplier over set the wholesale price compared with the theory, while in other treatments, the supplier under set the wholesale price compared with the theory.

3.6.3.3 Estimation Result 3: If the retailers have the market power, they are bounded rational when deciding the investment and the investment cost tolerance.

Comparing the bounded rationality results of investment and investment cost tolerance (γ_i) between different levels of the market power, we found that the retailers were bounded rational when having the market power, and when the retailers have no market power, they made the investment and investment cost tolerance decision randomly.

3.7 Discussion and Conclusion

This study investigates how the market power or changing of parametric settings can affect the supplier and the retailer strategic interactions in a dual channel complete information setting, through the lens of behavioral game theory and a series of controlled laboratory human-subject experiments.

We have three main findings. First, we find that the retailers were significantly affected by the market power. Different levels of market power result in different levels of impact to the retailer. Some may have a stronger impact on the retailer investment decision, while others impact on the retailer wholesale price decision.

Second, the suppliers were completely randomly making the wholesale price decisions. We observe such responses in all treatments.

Third, the behavioral model developed in this paper is able to capture and measure the impact of market power on the decisions, even when the strategic interactions of the supplier and the retailer are noisy and complex. Furthermore, numerical analyses based on the behavioral model establish a clear picture of how bounded rationality impacts investment decisions.

Our study explores market power in a dual channel as a motivator. Through a behavioral lens, we believe that our results offer novel insights that help in understanding the importance of the market power and investment in the supplier-retailer setting for practitioners. From a managerial perspective, this study suggests that although market power has no impact in the theory, it is an important aspect to consider in practice, because individuals are bounded rational.

The study is not without limitations. As one of the first studies to investigate the strategic interactions of the supplier and the retailer, including investment, wholesale, and investment tolerance, in a complete information dual channel setting. We opt for a simple design to focus on the key research questions. For example, we assume a complete information supply chain where all the relevant parameters such as probability of market power and private selling costs are known to all players when substantial asymmetric information may exist. Another example is that multiple suppliers and the retailers may exist in a competing form. We also assume the supplier has no capacity constraints where this is not always true in practice. From a methodological perspective, the study relies heavily on numerical predictions and controlled laboratory experiments. While the method is commonly accepted in the behavioral operations management, it is still not the same as field experiments, where every condition is real, and subjects have relatively strong background knowledge and experiences.

The limitations of the study suggest future extensions, along two directions. The first is to investigate how the market power and changing of parametric settings can affect the supplier and the retailer interactions in an asymmetry dual channel supply chain. The second is to study how multiple suppliers and retailers can affect the competitions.

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3.9 Chapter 3 Appendix

3.9.1 Chapter 3 Appendix A Proofs

We explained the details of model set up and list the steps of getting the equilibrium from the model.

3.9.1.1 Variables Used in the Model

Table 3.15: Variable Names

δ	Maximum demand
β	Demand sensitivity
c	Supplier production cost
c_s	Supplier direct marketing cost
I	Investment cost
c_i	Supplier product cost if Retailer invest in supplier production
c_r	Retailer marketing cost
δ_i	Increase in maximum demand if Retailer invest in total quality
q_s	Sales quantity of Supplier to market
q_r	Sales quantity of Retailer to market
w	Wholesale price

3.9.1.2 Game Theory Solution

The profit function from all three invest projects and the not invest decisions are listed in Section 3 in the model set up, in equation from (3.1) to (3.8). We solve our model starting by using backward induction to solve the best response sales quantity of supplier, q_s, and the best response sales quantity of retailer, q_r. The best response function of q_s and q_r are arguments that maximize the Supplier profit and the Retailer profit respectively. Note that the q_s and the q_r are the best response quantity given the wholesale price and the investment decision that Supplier and Retailer observe from the previous stage. Hence given the different investment decisions that Supplier and Retailer observe, the derivative needs to be calculated differently by each investment project. We only list one set of equations in

(3.17) as an example, which is to calculate the best response of q_s and q_r, given that the Retailer choose to invest in the Supplier production cost. Also, the wholesale price that the Supplier and the Retailer observe from the previous stage is the realized wholesale price, depending on the market power situation. We use w in the model to represent the realized wholesale price.

$$\begin{aligned} q_{r|1}^{BR} &= arg \max_{q_{r|1}} \left\{ (p - w - c_r)\, q_{r|1} - I \right\} \\ q_{s|1}^{BR} &= arg \max_{q_{S|1}} \left\{ (p - c_i - c_s)\, q_{s|1} + (w - c_i)\, q_{r|1} \right\} \end{aligned} \tag{3.17}$$

Solving equation set (3.17), we would be able to get the best response function of q_s and q_r for each investment project. We list all four different best response functions for q_s^{BR} and q_r^{BR} from equation (3.18) to (3.21). Each one of them is associated with one investment decision.

(1) Invest in supplier production

$$q_{s|1}^{BR} = \frac{\delta - 2c_i - 2c_s + c_r + w}{3\beta} \; and \; q_{r|1}^{BR} = \frac{\delta + c_i + c_s - 2c_r - 2w}{3\beta} \tag{3.18}$$

(2) Invest in retailer marketing cost

$$q_{s|2}^{BR} = \frac{\delta - 2c - 2c_s + w}{3\beta} \; and \; q_{r|2}^{BR} = \frac{\delta + c + c_s - 2w}{3\beta} \tag{3.19}$$

(3) Invest in total quality

$$q_{s|3}^{BR} = \frac{\delta + \delta_i - 2c - 2c_s + c_r + w}{3\beta} \; and \; q_{r|3}^{BR} = \frac{\delta + \delta_i + c + c_s - 2c_r - 2w}{3\beta} \tag{3.20}$$

(4) No investment

$$q_s^{BR} = \frac{\delta - 2c - 2c_s + c_r + w}{3\beta} \; and \; q_r^{BR} = \frac{\delta + c + c_s - 2c_r - 2w}{3\beta} \tag{3.21}$$

where w is the realized wholesale price depends on market power.

After solving for the best response function for sales quantity, we are backwards one more step to find the best response for wholesale price. The Supplier and the Retailer set up the wholesale price simultaneously. Hence, both Supplier and Retailer will set the wholesale price that maximizes his/her profit. Note that, similar as calculating the best response function for and q_s^{BR}, q_r^{BR} the best response function of wholesale price, w_s^{BR} and w_r^{BR} is the best response given the investment decision of the retailer in the previous stage. Therefore, we have four sets of best responses w_s^{BR} and w_r^{BR} for each different investment decision. In equation (3.23) and (3.22), we list the function to solve for the best response w_s^{BR} and w_r^{BR} when the Retailer chooses to invest in supplier production in the previous stage as an example.

$$w_{r|1}^{BR} = arg \max_{w_r} \left\{ a \left((p - w_r - c_r)\, q_{r|1}^{BR} - I \right) + (1 - \alpha) \left((p - w_s - c_r)\, q_{r|1}^{BR} - I \right) \right\} \tag{3.22}$$

$$w_{s|1}^{BR} = arg \max_{w_s} \left\{ a \left((p - c_i - c_s)\, q_{s|1}^{BR} + (w_r - c_i)\, q_{r|1}^{BR} \right) + (1 - \alpha) \left((p - c_i - c_s)\, q_{s|1}^{BR} + (w_s - c_i)\, q_{r|1}^{BR} \right) \right\} \tag{3.23}$$

Solving equation (3.23) and (3.22), we would be able to get the best response function of all four investment decisions and it is listed in the equation from (3.24) to (3.27).

(1) Invest in supplier production

$$\begin{gathered} w_{r|1}^{BR} = c_i \\ w_{s|1}^{BR} = \frac{1}{10}(5\delta + 5c_i - \mathrm{c}_s - 4\mathrm{c}_r) \end{gathered} \tag{3.24}$$

(2) Invest in retailer marketing cost

$$\begin{gathered} w_{r|2}^{BR} = c \\ w_{s|2}^{BR} = \frac{1}{10}(5\delta + 5c - \mathrm{c}_s) \end{gathered} \tag{3.25}$$

(3) Invest in total quality

$$\begin{aligned} w_{r|3}^{BR} &= c \\ w_{s|3}^{BR} &= \frac{1}{10}(5\delta + 5\delta_i + 5c - \mathrm{c}_s - 4\mathrm{c}_r) \end{aligned} \tag{3.26}$$

(4) No investment

$$\begin{aligned} w_{r}^{BR} &= c \\ w_{s}^{BR} &= \frac{1}{10}(5\delta + 5c - \mathrm{c}_s - 4\mathrm{c}_r) \end{aligned} \tag{3.27}$$

Using the best response wholesale price function, w_s^{BR} and w_r^{BR}, we will be able to find the Retailer profit function given different investment decisions and they are listed from equation (3.28) to equation (3.31).

(1) Invest in supplier production

$$\pi_{r|1} = \alpha\left(\frac{(\delta - \mathrm{c}_i + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta}\right) + (1-\alpha)\left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta}\right) - I \tag{3.28}$$

(2) Invest in retailer marketing cost

$$\pi_{r|2} = \alpha\left(\frac{(\delta - c + \mathrm{c}_s)^2}{9\beta}\right) + (1-\alpha)\left(\frac{4(\mathrm{c}_s)^2}{25\beta}\right) - I \tag{3.29}$$

(3) Invest in total quality

$$\pi_{r|3} = \alpha\left(\frac{(\delta + \delta_i - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta}\right) + (1-\alpha)\left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta}\right) - I \tag{3.30}$$

(4) No investment

$$\pi_{r} = \alpha\left(\frac{(\delta - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta}\right) + (1-\alpha)\left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta}\right) \tag{3.31}$$

The best response function of investment cost tolerance is calculated by finding the Retailer profit, given $I = 0$, for any given investment project, and the Retailer profit when

Retailer chooses not to invest. We listed the best response function for investment tolerance, given three investment decisions, in equation (3.32) to (3.34).

$$\begin{aligned} I_{r|1}^{BR} =& \alpha \left(\frac{(\delta - \mathrm{c}_i + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta} \right) + (1-\alpha) \left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta} \right) - 0 \\ & - \alpha \left(\frac{(\delta - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta} \right) - (1-\alpha) \left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta} \right) \end{aligned} \tag{3.32}$$

$$\begin{aligned} I_{r|2}^{BR} =& \alpha \left(\frac{(\delta - c + \mathrm{c}_s)^2}{9\beta} \right) + (1-\alpha) \left(\frac{4(\mathrm{c}_s)^2}{25\beta} \right) - 0 \\ & - \alpha \left(\frac{(\delta - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta} \right) - (1-\alpha) \left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta} \right) \end{aligned} \tag{3.33}$$

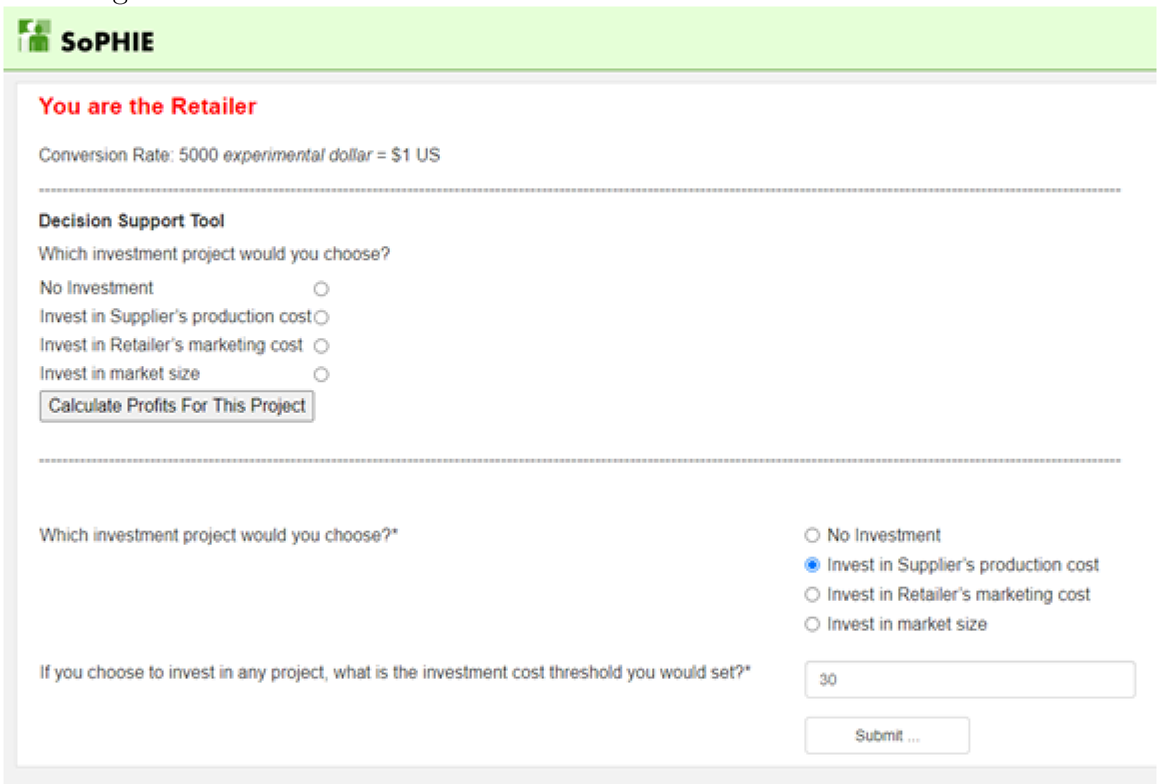
$$\begin{aligned} I_{r|3}^{BR} = & \alpha \left(\frac{(\delta + \delta_i - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta} \right) + (1-\alpha) \left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta} \right) - 0 \\ & -\alpha \left(\frac{(\delta - \mathrm{c} + \mathrm{c}_s - 2\mathrm{c}_r)^2}{9\beta} \right) - (1-\alpha) \left(\frac{4(\mathrm{c}_s - \mathrm{c}_r)^2}{25\beta} \right) \end{aligned} \tag{3.34}$$

Using the retailer profit function from equation (3.28) to (3.31), we would be able to find the equilibrium decision for the investment of the retailer. The equilibrium investment decision for Retailer is, to consider the same investment cost, I, and pick the investment that gives Retailer the highest profit.

In this appendix, we explained the process of finding the equilibrium of each decision of Supplier and Retailer and listed the equilibrium and best response function for each decision.

3.9.2 Chapter 3 Appendix B Experimental Screenshots

Figure 3.3: Retailer makes investment and investment tolerance decisions


SoPHIE

You are the Retailer

Conversion Rate: 5000 *experimental dollar* = $1 US

Decision Support Tool

Which investment project would you choose?

No Investment

Invest in Supplier's production cost

Invest in Retailer's marketing cost

Invest in market size

Calculate Profits For This Project

Which investment project would you choose?*

No Investment

Invest in Supplier's production cost

Invest in Retailer's marketing cost

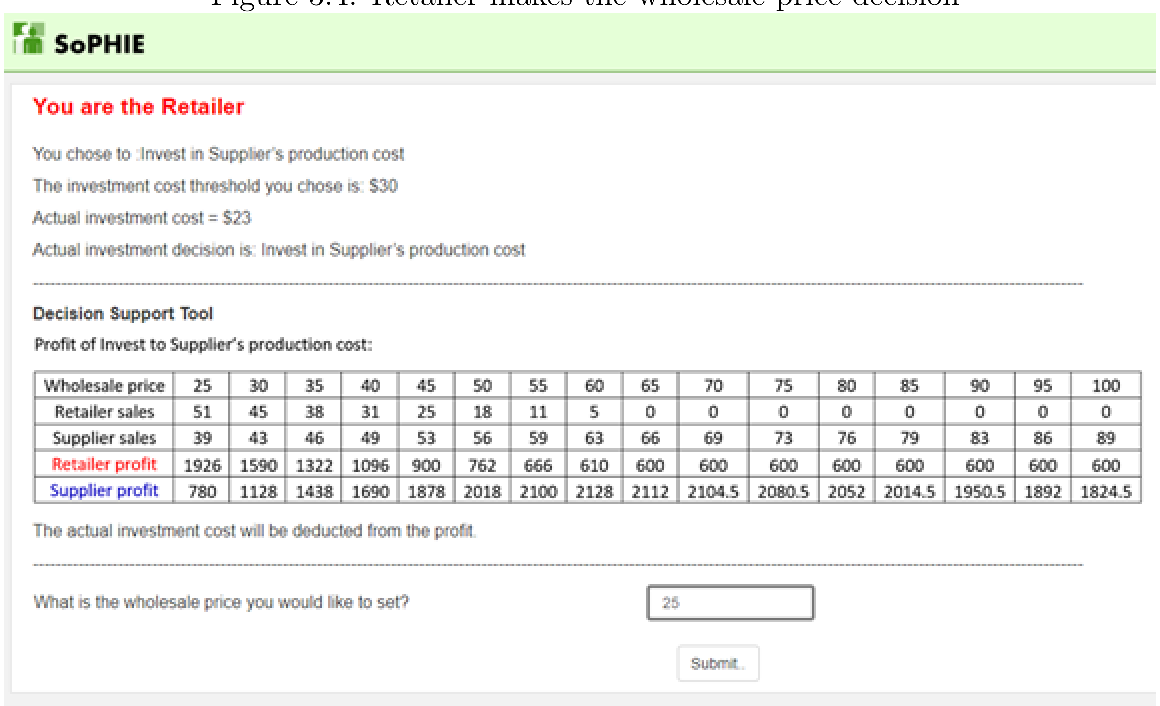
Invest in market size

If you choose to invest in any project, what is the investment cost threshold you would set?*

30

Submit ...

Figure 3.4: Retailer makes the wholesale price decision


SoPHIE

You are the Retailer

You chose to :Invest in Supplier's production cost

The investment cost threshold you chose is: $30

Actual investment cost = $23

Actual investment decision is: Invest in Supplier's production cost

Decision Support Tool

Profit of Invest to Supplier's production cost:

Wholesale price	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
Retailer sales	51	45	38	31	25	18	11	5	0	0	0	0	0	0	0	0
Supplier sales	39	43	46	49	53	56	59	63	66	69	73	76	79	83	86	89
Retailer profit	1926	1590	1322	1096	900	762	666	610	600	600	600	600	600	600	600	600
Supplier profit	780	1128	1438	1690	1878	2018	2100	2128	2112	2104.5	2080.5	2052	2014.5	1950.5	1892	1824.5

The actual investment cost will be deducted from the profit.

What is the wholesale price you would like to set?

25

Submit.

Figure 3.5: Supplier makes the wholesale price decision

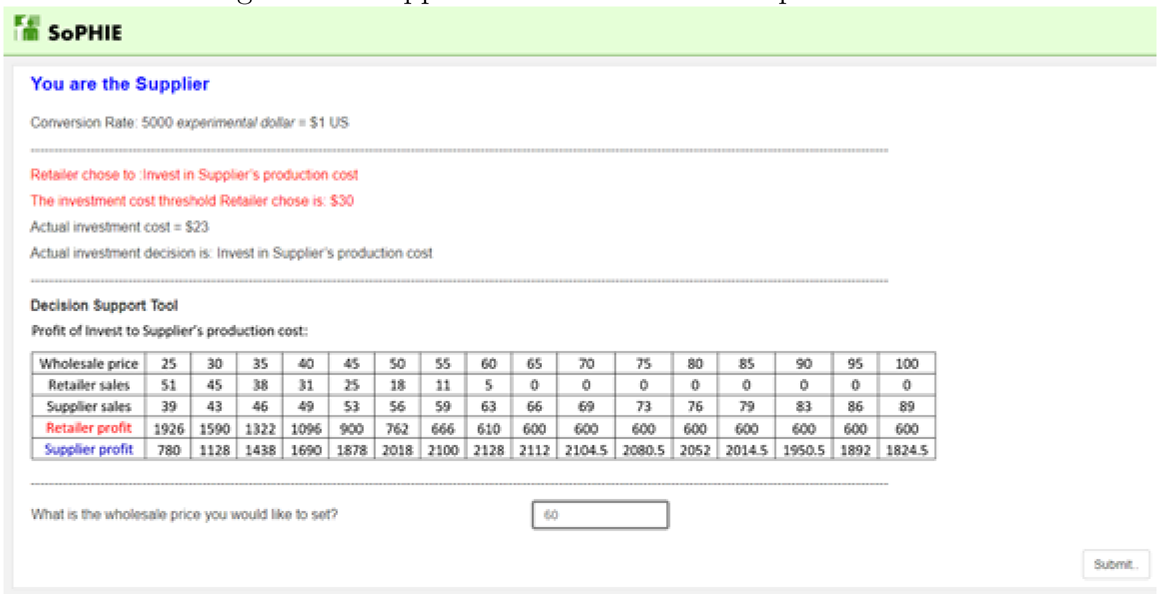


Figure 3.6: Retailer show profit

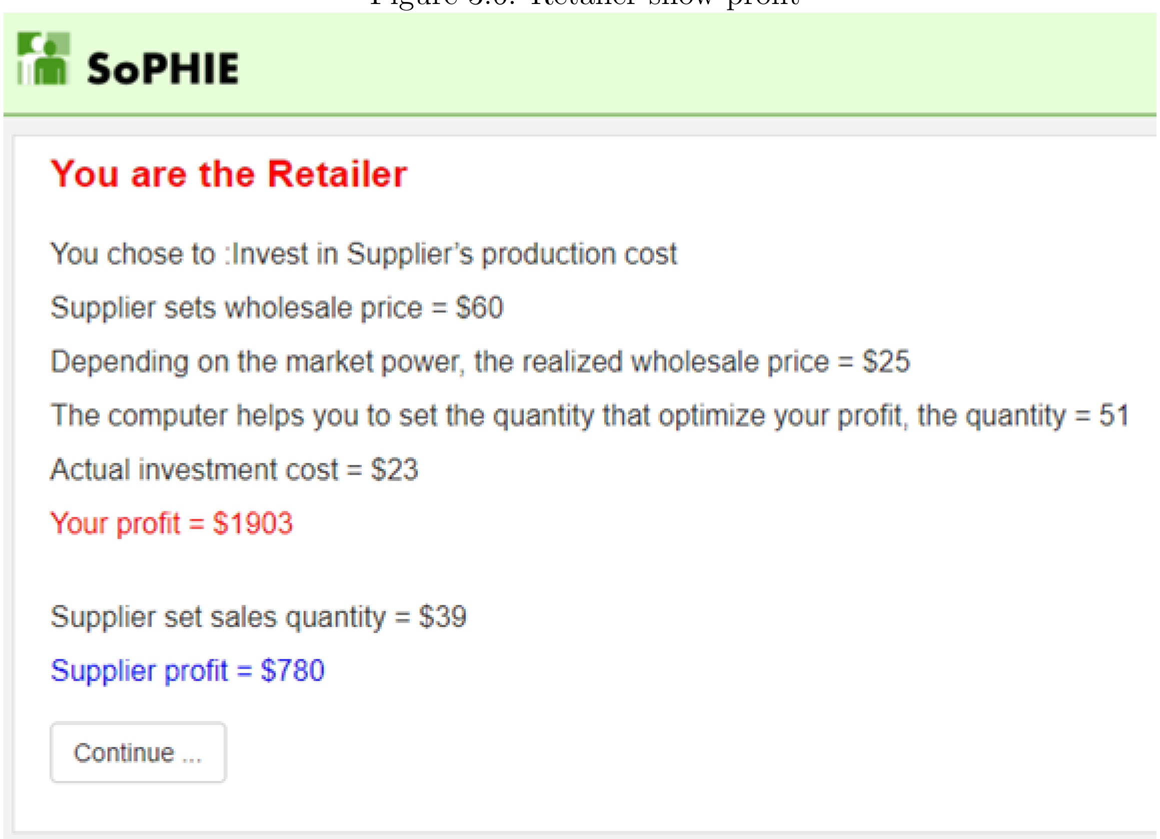
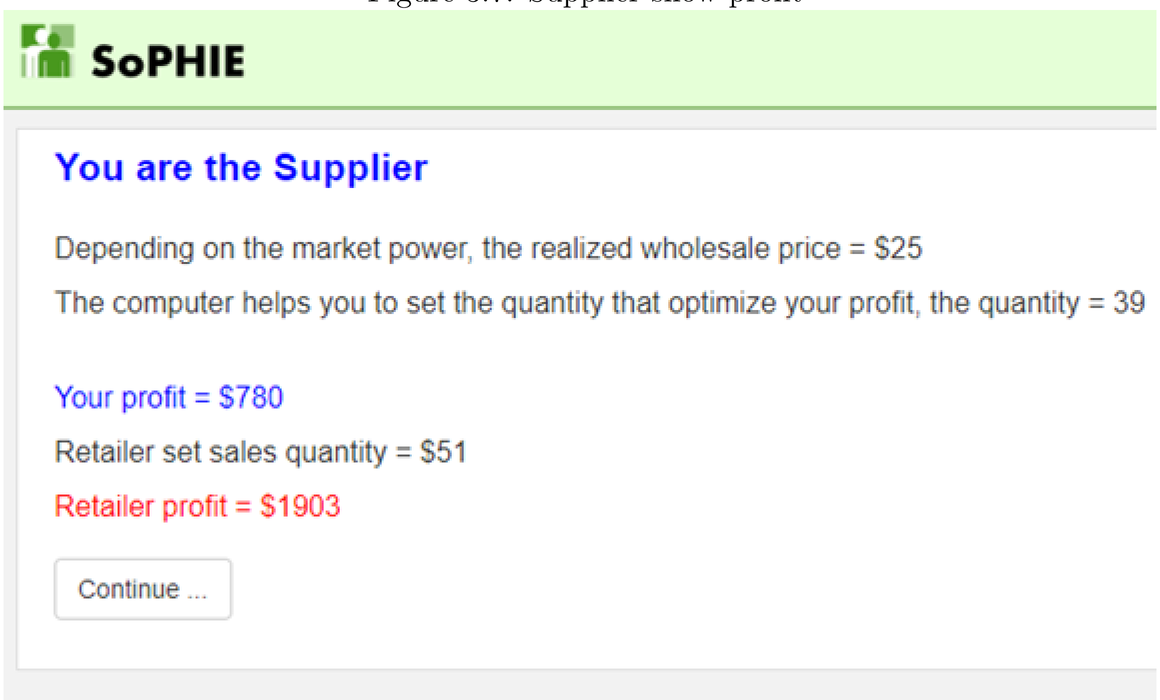


Figure 3.7: Supplier show profit



CHAPTER 4

Design Optimal Fuzzy Return for Retailer

Jingjie Su, Narayanan Janakiraman, Kay-Yut Chen

College of Business, The University of Texas at Arlington

4.1 Introduction

Due to the fast growth of internet technology and e-commerce, we have seen some significant changes in the retailer business in the past few years. According to news article from the New York Times, more than 40% of traditional retail businesses have adopted a multi-channel sale strategy (Tedeschi, 2000), and their online sales are expected to increase from $100 billion in 2010 to $170 billion in 2015 (Pei et al., 2014). Because of the physical limitation of online shopping, consumers are unable to touch, feel, or inspect the product. This increases the likelihood of dissatisfaction with the consumer purchase and the probability of returning the product (Mukhopadhyay & Setaputra, 2007).

Despite the cost and prevalence of returns, many retail companies offer different kinds of product return policies available to their consumers, and hope to hedge the cost of the return by the revenue gain from the increase in sales. One of the most challenging problems sales managers face today is how to design a consumer return policy. When should a firm adopt a simple return policy or when should it use a more complex return policy? Furthermore, because there are many types of complex return policies available, which of these contracts should the firm choose? To answer these questions, scholarly research mainly focus on consumers attitude towards the return policy set by retailer (Janakiraman & Ordóñez, 2012; Janakiraman et al., 2016; Pei et al., 2014). Wang et al. (2012) discuss a special type of return called fuzzy return, defined as the return request that is slightly outside the regular acceptance policy for the retailer, yet to be completely unacceptable and might provide a friendlier and effortful outcome.

Along this line of thought, we take the perspective of the retailer and design the study to explore the potential of fuzzy return as a solution to the increasing cost of consumer return problem. Given the complexity of the strategic interactions in consumer return setting, and the multiple incentives and decisions in play, the goals of the paper are to investigate: (1) can we show the fuzzy return benefits the retailer under certain conditions? (2) How the fuzzy return impacts the consumer decisions.

Game theoretical analysis reveals that the retailer should set up two different types of fuzzy return policy, depending on the product uncertainty and consumer learning rate. If the product uncertainty is high and the consumer has a low learning rate, the retailer should offer a fuzzy return, which is to accept a proportion of return during the fuzzy return stage. If the product uncertainty is low, the retailer should offer a short return, which is to accept no return during the fuzzy return stage. We have identified the condition, in the function of production uncertainty and consumer learning rate, to separate two strategies of the retailer. We simulate the process of the model. The result matches the game theoretical prediction. From the simulation, we also observe the increase of the degree for the fuzzy return acceptance rate as the increase of product uncertainty. Furthermore, we introduce signaling effect into the model. The signaling effect occurs when the retailer offers a long return, which is to accept all return during the fuzzy return stage. With game theoretical analysis, we find that the fuzzy return policy is divided into four different strategies in the signaling effect model. In addition to the result in the model without signaling effect, the retailer should offer a long return, which is to accept all return in the fuzzy return stage in another two conditions. We identified the condition to separate these four strategies. From the game theoretical analysis and model simulation, we conclude that, the retailer should offer different strategies, depending on the different product uncertainty and consumer learning rate, in both model with and without signaling effect.

The rest of the paper is structured as follows. Section 4.2 summaries the related literature in modeling for return or fuzzy return policy. Section 4.3 introduces the model set up and provides the theoretical proposition of the model. Section 4.4 includes the simulation and model implication. We conclude our findings and make suggestion for future study in Section 4.5.

4.2 Literature Review

We discuss three streams of literature that are relevant to this research: modeling for return policy, fuzzy return, and consumer learning.

The first stream of literature is the modeling for the return policy. There are many papers discussing the model for the return policy (Hu et al., 2019; Ofek et al., 2011; Tran et al., 2018). Some of these papers study the impact of return policy and retailer profit. For example, Ofek et al. (2011) modeling about how the return policy can affect the sales if the retailer choose to open both online and physical store channels. They find that the return policy is actually reducing the retailer profit when both online and physical channels are initiated. Hu et al. (2019) build a model to test the return policy under the monopoly dynamic pricing structure. Their model suggests that the product return should not be ignored by the seller, otherwise, it could lead to profit loss. They also develop an optimal return policy to serve as a purpose of seller guidelines. Other papers focus on the return policy between the supplier/manufacturer and retailer. Tran et al. (2018) explore the preference for the manufacturer between the quota-based versus partial-refund policy. Their model shows that the manufacturer is facing higher variation in profit when adopting partial-refund policy. Our paper adds to the literature by modeling the return policy between the retailer and consumer. More specifically, we focus on the part of policy, which is not covered by the standard return policy in the company.

The second stream of literature is the fuzzy return. Literature for fuzzy return is growing in numbers now. Wang et al. (2012) describe the fuzzy return request as the return request that is slightly outside the regular acceptance policy for the retailer, yet to be completely unacceptable. They design the survey for the retailer manager to study how they handle this kind of fuzzy request. Their result suggests that the attitude of consumers, as well as the attitude of the firm, are two major considerations when a retailer manager is dealing with the fuzzy return. Li et al. (2018) focus on finding the relationship between the outcome of managers towards the fuzzy return and consumers behavior during the request. Their empirical result indicates a positive relationship between consumers emotions with mangers acceptance rate for the fuzzy return. Our model for fuzzy return is inspired from the fuzzy request in their paper. And we take the perspective of the retailer and look at the attitude of the retailer towards the fuzzy request of return from consumers. We refer to this fuzzy request of return as “fuzzy return” in the paper and the return request which is completely acceptable by the company policy as “regular return”. To our best knowledge, most fuzzy return papers are empirical studies and we are the first to make a mathematical model to study this type of return.

The last stream of literature is consumer learning. Hoch and Deighton (1989) argue that the consumer learning process includes four steps: hypothesizing, exposure, encoding and integration. They also identify three factors that affect the consumer learning, including (1)how familiar the consumer is to the product, (2) is the consumer motivated to learn the product and (3) is the product information clear enough. Akçura et al. (2004) studies consumer learning towards brand valuation. Their result suggests that consumers could learn the value of the brand over time. They also indicate, once the brand value is learned, consumers are less sensitive to the price. Erdem et al. (1999) explores the linkage between brand equity and consumer learning. They argue that the consumers learn the value of the product and brand so that they have developed an incremental utility of the brand. All papers focus on how the consumer learning is affected by the different factors or how consumer learning affects their purchase decision. We extend the single period purchase decision to dual period, which involves the return as one option. And we check the relationship between consumer learning with the set-up of return policy by the retailer.

We believe that our paper is unique, combining the mathematical model with return policy and consumer learning. Through the model and the simulation, our paper brings a new perspective in studying the return policy.

4.3 Model Set Up

We build a four-stage complete information retailer setting model with one retailer and a population of consumers. Wang et al. (2012) describes a situation which is defined as a fuzzy request of return from consumer in their paper. This fuzzy request happens when consumers request a return that is outside the policy of company but not completely unacceptable to the Retailer. In our model, we assume the consumer has already purchased the product and he/she has two opportunities to return the product. The first one is within the regular return stage and the Retailer is guaranteed to accept the consumer return. Another one is after the regular return stage and the Retailer has a probability to accept the return. We define the latter one to be the fuzzy return stage and the probability to be the fuzzy return policy. The value of the product is unknown to the consumer at the time of purchase. Consumer gets one update of product value by observing an additional signal of product value, during his/her usage of the product within the regular return stage. We further assume that, at the time consumers can decide on the fuzzy return, they already know the true value of the product. We frame our model from the perspective of the Retailer who is trying to determine the optimum fuzzy return policy, which is the probability, to maximize his profit. And the consumer, after observing the fuzzy return policy from the Retailer, can choose between purchase but return the product within regular return stage, purchase but request the fuzzy return after regular return stage and purchase and keep the product. Consumers make their decisions individually by maximizing their individual expected utility from each decision.

The model consisted of four stages.

Stage 1: Retailer decides the fuzzy return policy, which is the probability that Retailer accepts the fuzzy request from consumer (q).

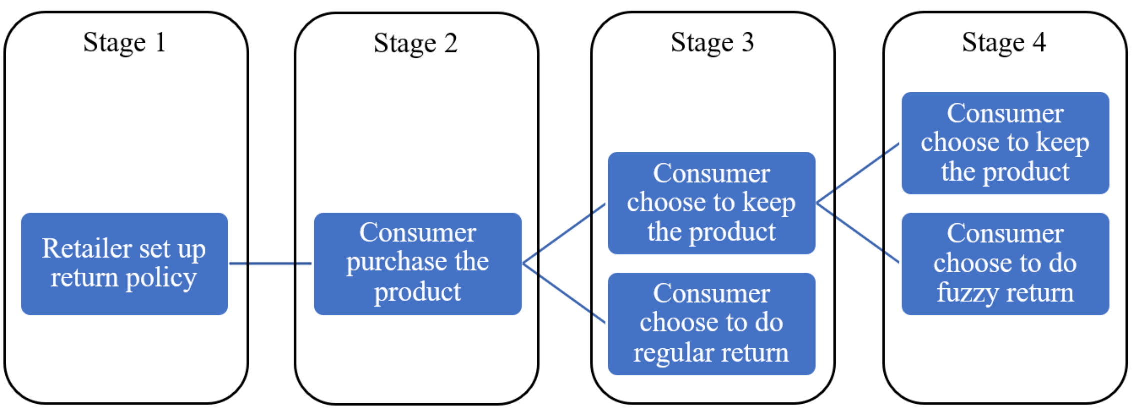
Stage 2: Consumers purchase the product.

Stage 3: Within the regular return stage, consumers can choose to keep or return the product. If a consumer chooses to keep the product within the regular return stage, he/she proceeds to the next step. If a consumer chooses to return the product, he/she exits the model with a regular return.

Stage 4: After the regular return stage, consumers can choose between continuing to keep the product or request a fuzzy return.

Since the Retailer is facing the entire market of consumers and each consumer can go through the game process from stage 2 to stage 4, each consumers can make different decisions from stage 2 to stage 4 and their decisions are all independent to each other. We demonstrate the return process in Figure 4.1.

Figure 4.1: Return Process

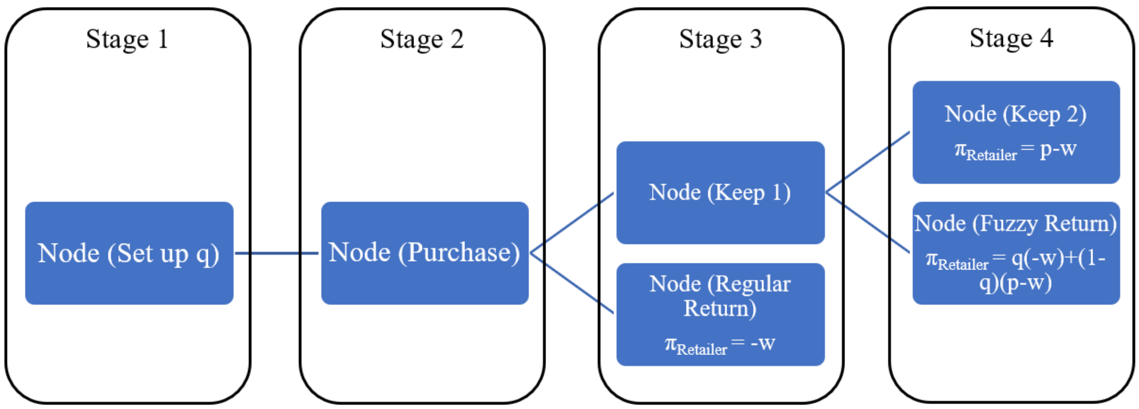


Our model focuses on the Retailer side and tries to analyze the optimal fuzzy return policy that the Retailer should set up in stage 1, in order to generate the most profit.

4.3.1 Retailer Profit Component

Retailer gets the profit by selling the product to consumers with the market price (p) and the cost for the Retailer is the wholesale price (w). We assume that if the product is returned, the product cannot be resale and the salvage value of the returned product is 0. Depending on the different decisions from consumers, the profit of Retailer comes from each branch is shown in Figure 4.2.

Figure 4.2: Retailer Process with Retailer Profit



The first branch is from consumers who choose to do the regular return in stage 3 at Node (Regular Return). Retailer pays a full refund of the product price to the consumer. Since there is no salvage value and the product is non-resalable, Retailer has a loss of wholesale price for the product. The profit of Retailer is $\pi_{Retailer}^{Regular\ Return} = -w$ from each consumer choose to do a regular return the product in stage 3. The second branch is from consumers who choose to keep the product in stage 4 at Node (Keep 2). Retailer gets the profit of product price minus the wholesale price in this branch. The profit of Retailer is $\pi_{Retailer}^{Keep\ 2} = p - w$ from consumers choose to keep the product in stage 4. The third branch of Retailer profit is from consumers who choose to do fuzzy return in stage 4 at Node (Fuzzy

Return). Retailer has a probability of accepting or denying the return from consumers in this node. If Retailer accepts the fuzzy return, the profit of Retailer is $-w$, since Retailer gives a full refund of the product to consumer and has a cost of wholesale price, w. If Retailer denies the fuzzy return, Retailer gets the product price, p, as the revenue and the cost of the product is the wholesale price, w. This probability is set by Retailer in stage 1 and it is defined as q, where q is between 0 and 1, $0 \leq q \leq 1$. So the expected profit of Retailer in this branch is $\pi_{Retailer}^{Fuzzy\ Return} = q(-w) + (1-q)(p-w)$. Since Retailer is facing a continuum of consumers, his total profit is equal to the proportion of consumers in each branch times the profit that Retailer gets from that branch and it is shown in equation (4.1).

$$\begin{aligned} \pi_{Retailer} =& \%\ of\ Regular\ Return \times (-w) + \%\ of\ Keep \times (p-w) \\ &+ \%\ of\ Fuzzy\ Return \times (q(-w) + (1-q)(p-w)) \end{aligned} \tag{4.1}$$

The next step is to determine the proportion of consumers in each branch. This proportion is depending on consumers' decision during stage 2 to stage 4. We use the next section to explain how consumers make decisions from stage 2 to stage 4.

4.3.2 Consumer Process

We model a population of consumers who have already purchased the product. Consumers are risk neutral and trying to maximize his/her expected utility. Each consumer has a value of the product which is not known to them at the time of purchase. We assume a prior distribution of the belief of the product value. After a consumer purchases the product, he/she will receive a random signal of the product value during his/her usage within the regular return stage. With this signal, the consumer updates his/her product value distribution to a posterior distribution, with the Bayesian distribution update rule.

Based on the posterior distribution, the consumer could choose to keep or proceed with the regular return of the product. If the consumer chooses to keep the product, after the regular return stage, he/she will learn the true product value and can choose to continue to keep the product or proceed to request the fuzzy return. The return will either be accepted or denied and it is a random choice by Retailer.

Figure 4.3: Consumer Process with Consumer Utility

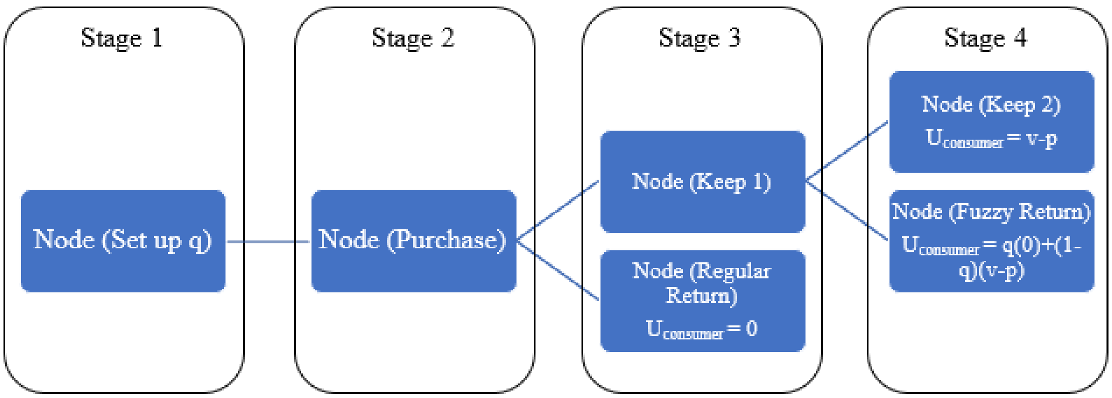


Figure 4.3 shows the consumer process with the utility of each node. Starting on stage 2, consumers purchase the product from the retailer. Consumer has a prior distribution of the product value, $v_{prior} \sim N(\mu_0, \sigma_0^2)$, before they make the purchase. The σ_0^2 is defined as the variance of the prior distribution of consumer value for the product. As the σ_0^2 could be viewed as the product fit uncertainty, where a high σ_0^2 indicates that consumers have more uncertainty that the product is going to fit their value before they purchase and a low σ_0^2 indicates that consumers have less uncertainty about the product fit. Nelson (1974) defined the low uncertainty in product fit as the "search product" and high uncertainty product fit as the "experience product". We use the same term in this paper.

Consumer pays for the product with the product price, p. After the consumer purchases the product, he/she moves through Node(Purchase) into stage 3, which is the regular return stage. During the regular return stage, consumers will have an update of the product value in stage 3. This update is through the signal that the consumer receives during this regular return stage. The signal,s, is drawn from an error distribution, which is normally distributed, $s \sim N(\mu_0, \sigma_e^2)$. The σ_e^2 is defined as the variance of the signal distribution. A high σ_e^2 indicates that the consumer is less certain about the product value through his/her usage within the regular return stage and a low σ_e^2 is vice versa. Consumer updates his/her posterior distribution of product value, $v_{posterior} \sim N(m, \sigma_v^2)$, based on the randomly drawn signal s. The resulting formula m and σ_v follows the rule of the Bayesian update rule and it is shown in equation (4.2) and (4.3).

$$\sigma_v^2 = \frac{\sigma_0^2 \sigma_e^2}{\sigma_0^2 + \sigma_e^2} \tag{4.2}$$

$$m = \frac{\sigma_e^2}{\sigma_0^2 + \sigma_e^2}\mu_0 + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_e^2}s \tag{4.3}$$

From the above equations, we can learn some properties of the posterior distribution. If the error distribution has a lot of noise, which is represented with a high σ_e^2, the posterior distribution will also have a lot of noise, which results in a high σ_v^2. A less noisy error distribution with a low σ_e^2 will result in a less noisy posterior distribution with a low σ_v^2. And the mean of the posterior distribution is a linear combination between the mean of prior distribution, μ_0, and the randomly drawn signal, s. The center of posterior distribution is always between μ_0 and s and it is moving from the center of prior distribution towards the signal. The distance of moving depends on the σ_0^2 and σ_e^2 in equation (4.3).

Based on the posterior distribution of product value, the consumer makes decision between keeping the product or returning the product within the regular return stage. If the consumer chooses to keep the product, he/she continues to move to stage 4 through Node (Keep 1). If the consumer chooses to return the product, the consumer proceeds the regular return in Node (Regular Return), in which he/she receives a full refund of the product and the utility of the consumer is 0.

If the consumer choose to keep the product and proceed to stage 4, which is the fuzzy return stage. In this stage, the consumer observes the value of product, v, where v is randomly drawn from the posterior distribution of value, $v_{posterior} \sim N(m, \sigma_v^2)$. Upon observation of value v, the consumer chooses between continuing to keep the product or return to the retailer. If the consumer chooses to continue keep the product, he/she moves to Node (Keep 2), exists the process and end up with purchase the product, with the utility $U_{Consumer}^{Keep\ 2} = v - p$. v is the value of the product that consumer receives and p is the product price. If the consumer chooses to return to the retailer, he/she moves to Node (Fuzzy Return) and will receive the fuzzy return of the product, meaning that retailer has an option to deny this return. If Retailer accepts the return, the consumer will get a full refund and the utility of the consumer is 0. If Retailer denies the return, the consumer would have to keep the product and the utility of the consumer is $v - p$, where v is the product value and p is the product price. The probability of Retailer to accept this fuzzy request of return is q, so the expected utility of consumer in this node is $U_{Consumer}^{Fuzzy\ Return} = q(0) + (1 - q)(v - p)$.

In order to find the proportion of consumers into each branch, we need to use backward induction to solve the game. We start the calculation from stage 4 and move backwards to stage 3, then stage 2. At stage 4, the consumer will keep the product if the utility of keep the product at Node (Keep 2) is higher than the expected utility of fuzzy return at Node (Fuzzy

Return), $U^{Keep\ 2}_{Consumer} > U^{Fuzzy\ Return}_{Consumer}$. This means the consumer will keep the product if $v > p$. Depending on the randomly drawn product value, v, that consumer receives during the stage 4, there will be some consumers who choose to keep the product and some consumers choose to do the fuzzy return. And then at stage 3, the consumer will keep the product if the expected utility of keep at Node (Keep 1) is greater than the utility of regular return at Node (Regular Return), where the expected utility of keep at Node (Keep 1) is calculated with equation (4.4). Since the utility of consumer for regular return is $U^{RegularReturn}_{Consumer} = 0$, Consumer will keep the product at stage 2 when $E(U^{Keep\ 1}_{Consumer}) > 0$.

$$\begin{aligned} E(U^{Keep\ 1}_{Consumer}) &= \int_{-\infty}^{p} (q(0) + (1-q)(v-p))\, f(v)\, dv + \int_{p}^{\infty} (v-p)\, f(v)\, dv \\ &= m - p - q\left(m - \sigma_v \frac{z(t)}{Z(t)}\right) F(p) + q \cdot p \cdot F(p) \end{aligned} \tag{4.4}$$

Where the $f(v)$ and $F(v)$ are the probability density function and cumulative density function of posterior distribution, $v_{posterior}$, respectively. $t = \frac{p-m}{\sigma_v}$. $z(t)$ and $Z(t)$ are the standard normal probability density function and cumulative distribution function of standard normal distribution of t.

We define s^* as the signal cut point such that if consumer receive the signal $s > s^*$, the $E(U^{Keep\ 1}_{Consumer}) > 0$ and the consumer will keep the product at stage 3. If at stage 3, consumer receives the signal $s < s^*$, the $E(U^{Keep\ 1}_{Consumer}) < 0$ and the consumer will proceed with regular return at Node (Regular Return). Depending on randomly drawn signal s, there will be some consumers choose the keep the product at stage 3 and other consumers choose to process regular return.

From the above equations, we can find that depending on the product variables, including μ_0, σ_0^2, σ_e^2, consumers will go to different branches. This will result in a change proportion of the profit of Retailer from each branch. Detailed calculation can be found in Appendix A.

4.3.3 Retailer Profit Calculation

We use the proportion of consumer decisions which are defined in the previous section to continue to find the profit of Retailer. From the previous section, we can update the Retailer profit split in equation (4.1).

Depending on the choice from consumers, Retailer will end up getting 3 types of profit. The proportion of consumers choose to proceed regular return at stage 3 is $Proportion\ of\ Regular\ Return = \int_{-\infty}^{s^*} g(s)\, ds$, which is a summation of consumer who receives the signal less than s^*, $s < s^*$,. The proportion of consumers choose to keep the product at stage 4 is $Proportion\ of\ Keep\ 2 = \int_{s^*}^{\infty} (1 - F(p))\, g(s)\, ds$. This proportion is a summation of consumer who receives the signal greater than s^*, $s > s^*$, at stage 3 and has the true product value greater than product price, $v > p$, at stage 4. And last part is the proportion of consumers choose to do fuzzy return at stage 4 and it is equal to $Proportion\ of\ Fuzzy\ Return = \int_{s^*}^{\infty} F(p)\, g(s)\, ds$, which is the summation of consumer who receives signal greater than s^*, $s > s^*$, at stage 3 and has the true product value less than product price, $v < p$, at stage 4. We summarize the Retailer profit in equation (4.5). Retailer set up the fuzzy return policy (q) in order to maximize his profit.

$$\pi_{Retailer} = (-w) \int_{-\infty}^{s^*} g(s)\, ds + (q(-w) + (1-q)(p-w)) \int_{s^*}^{\infty} F(p)\, g(s)\, ds + (p-w) \int_{s^*}^{\infty} (1-F(p))\, g(s)\, ds \tag{4.5}$$

4.3.4 Model with Signaling Effect

We extend our model to add an signaling effect to the base model. According to Wood (2001), consumers have a higher belief of product value depending on the return policy of the Retailer. In the signaling effect model, we assume that, in stage 1, if the Retailer sets the fuzzy return policy to be long return, which is $q = 1$, consumers receive a signal about the quality of the product. When the Retailer decides to accept all return outside the regular return stage, $q = 1$, the consumer has a higher value distribution for the product. This assumption matches the literature, which states that consumer has a higher belief of product value when Retailer offers better return policy. In the model set up, this indicates that, when the Retailer sets up the return policy to be long return, the consumer has a higher prior distribution for the product. When $0 \leq q < 1$, consumer has same prior distribution for the product value as in the base model, $v_{prior|0 \leq q<1} \sim N(\mu_0, \sigma_0^2)$. When $q = 1$, the consumer has a higher expected value of the prior distribution for the product value, $v_{prior|q=1} \sim N(\mu_1, \sigma_0^2)$ and $\mu_1 > \mu_0$. To differentiate, we define the latter distribution $v_{prior|q=1} \sim N(\mu_1, \sigma_0^2)$ follows the probability density function of $h(v)$ and cumulative distribution function of $H(v)$. In stage 2, 3 and 4, the consumer follows the same process as in the base model. The Retailer follows the same process as in the base model to calculate the profit.

In this section, we have set up the mathematical model for the return policy.

4.4 Result and Model Implication

In this section, We find the game theoretical prediction for our model and then use the numerical simulation to demonstrate the main finding from the prediction.

In this section, we define a new term, learning rate to make the model implication easier to understand. Learning rate is defined as, $l = 1 - \frac{\sigma_e^2}{\sigma_0^2}$, which more directly reflects the relationship between σ_0 and σ_e. Learning rate is reflected as the reduction of value variance from the prior distribution to the posterior distribution. The high l indicates the consumers being able to resolve more uncertainty within the regular return stage through product trial and the low l indicates the consumers resolve a small proportion of uncertainty of the product. We define the high l consumers as fast learning consumers and low l consumers as slow learning consumers.

4.4.1 Base Model Result

We start with the base model. We solve the game theory prediction for the model using backward induction and list the following propositions. The detailed model solving process and prove can be found in Appendix A.

Proposition 1a: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, if the conditions satisfy in following equation (4.6)*, the optimal fuzzy return policy is to offer short return, meaning that $q^* = 0$.*

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} < 0 \tag{4.6}$$

Proposition 1b: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, if the conditions satisfy in equation (4.7)*, the optimal fuzzy return policy is to offer fuzzy return, meaning that $0 < q^* < 1$.*

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} > 0 \tag{4.7}$$

Proof:

We only consider the product price that is less than the mean of distribution for consumer value because, in real life, there is not much product that has higher value than the expected value of the consumer.

To find the optimal strategy of fuzzy return, q^*, we calculate the derivative of the Retailer profit, $\pi^{1.2R}_{Retailer}$, over our decision variables, q , at two end points of q, which is $q = 0$ and $q = 1$.

The derivative of the end point when $q = 1$ is shown as the following equation (4.8). Note that, the derivative at this end point is always negative.

$$\begin{aligned}
&\frac{d\pi^{1.2R}_{Retailer}(q=1)}{dq} = -p \cdot g(s^*(q=1,\sigma_0,\sigma_v,p))\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \\
&+ F(s^*(q=1,\sigma_0,\sigma_v,p)) \cdot g(s^*(q=1,\sigma_0,\sigma_v,p))\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \cdot p \\
&+ (-p)\int_{s^*(q=1,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)\, ds
\end{aligned} \tag{4.8}$$

The derivative of another end point when $q = 0$ is shown as following equation (4.9). This derivative can be positive and negative based on the product characteristic (σ_0 and σ_e).

$$\begin{aligned}
\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} =& -p \cdot g(s^*(q=0,\sigma_0,\sigma_v,p))\frac{ds^*(q=0,\sigma_0,\sigma_v,p)}{dq} \\
&+ (-p)\int_{s^*(q=0,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)\, ds
\end{aligned} \tag{4.9}$$

The above results indicate that the return policy is a conditioned strategy. For a given product characteristics (σ_0) and consumers type (σ_e), if it satisfies the condition that $\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} < 0$, the model has corner solution, which is $q^* = 0$. For a given product characteristics (σ_0) and consumers type (σ_e), if the condition that $\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} > 0$ is satisfied, the model has interior solution, which is $0 < q^* < 1$. Detailed proof can be found in Appendix

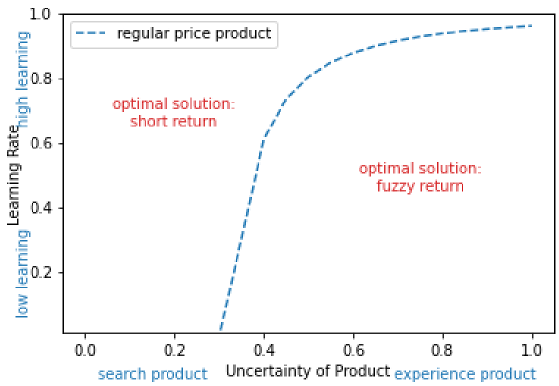
A.

4.4.1.1 Observation 1: Depending on different product uncertainty and consumers' learning rate, Retailer should offer either short return or fuzzy return in the base model.

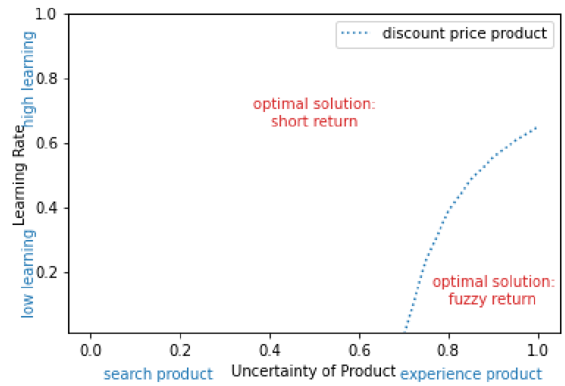
To demonstrate the finding, we artificially pick some values of mode for the simulation to see how the model implicates the action of Retailer in real life. The parameters include, μ_0, σ_0, σ_e, w and p. Consumers' value distribution has an expected value, $\mu_0 = 1$. Both variance of prior and posterior for consumers' value distribution is between 0 and 1, $0 < \sigma_0 < 1$ and $0 < \sigma_e < 1$. Retailer wholesale for the product of the $w = 0.5$. We pick two prices to do the simulation, one is $p_1 = 0.9$ and another is $p_2 = 0.8$. We pick these prices for two reasons. Firstly, both prices are less than the expected value of consumer value distribution, which fits our assumption in Proposition 1 and 2. Secondly, by including two prices, we can see how different prices can change the degree of optimal solution of the model. To make it simple to demonstrate, we call the product that has $p_1 = 0.9$ to be the regular price product and the product that has $p_2 = 0.8$ to be the discount price product.

In Figure 4.4, we simulate the strategy mapping for the Retailer, given two different prices. The Figure 4.4(a) is the graph for the regular price product and Figure 4.4(b) is for the discount price product. The horizontal axis for both graphs is the uncertainty of the product, which is measured by σ_0. A small σ_0 indicates the product type is a search product and a large σ_0 indicates the product type is an experience product. The vertical axis of the mapping is the learning rate, where learning rate is measured by $l = 1 - \frac{\sigma_e^2}{\sigma_0^2}$. A small learning rate means the consumer has a lower ability to resolve the uncertainty of the product within the regular return stage and a large learning rate is vice versa.

Figure 4.4: Strategy Mapping



(a) Strategy Mapping for Regular Price Product



(b) Strategy Mapping for Discount Price Product

In both graphs, the line separates the entire mapping into two parts. The left part is where the optimal return policy for Retailer is to always use a short return and the right part of the graph is where the optimal return policy for Retailer is to use a fuzzy return. From Figure 4.4(a) and 4.4(b) we have the following observations.

From both Figures, we can see that at some certain learning rate, if the uncertainty of the product is low, the Retailer should offer a short return. If the uncertainty of the product is high, the Retailer should offer a fuzzy return. The intuition behind this observation is that, when the uncertainty of the product is low, consumers have less variation of the product in the initial purchase. They already know if they are going to keep or return the product before they enter the stage 3. In that case, it is unnecessary for the Retailer to offer the fuzzy return to stimulate consumers to keep the product. On the other hand, if the uncertainty of the product is low, Retailer should offer some degree of accepting fuzzy return to push consumers to keep the product.

Another observation we find from the Figure 4.4(a) and 4.4(b) is that, for certain products, Retailer should offer a fuzzy return if their customers are considered to be low learning. If their customers are considered to be with high learning, Retailer should offer just a short return. The intuition behind this observation is that, when the consumers are considered to be low learning, this indicates they have higher variance, σ_e^2, in the posterior distribution. A high variance in the posterior distribution means that consumers learn very slow about the product value and the Retailer should offer the fuzzy return to stimulates sales.

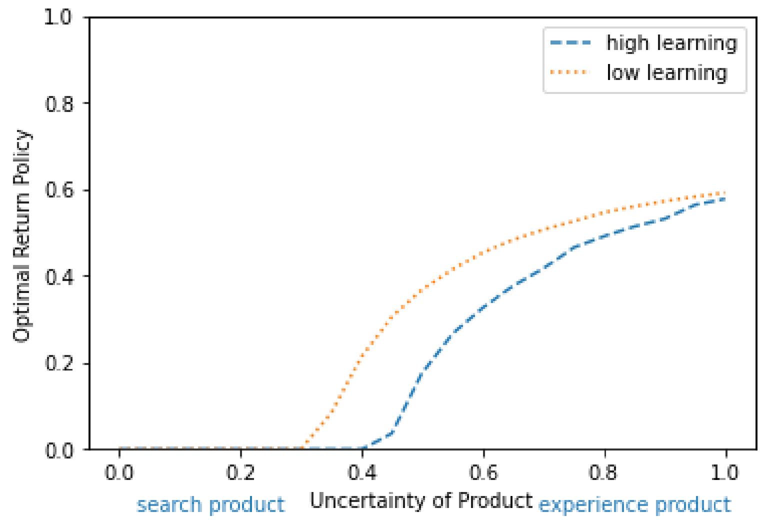
What we suggest from these observations is that Retailer should adopt different return policies for different products. For example, we define the computer as the search product and the cloth as the experience product, as suggested by Luan et al. (2016). As a Retailer, like Walmart or Costco, they should adopt a more strict return policy, such as a short return policy, for computers. And they should adopt more lenient policy for the cloth, such as allowing higher probability of accepting fuzzy return. And also, for the same experience product, such as cloth, if it is charging a lower price in Walmart than in Costco, Walmart should adopt a more strict return policy than Costco does.

4.4.1.2 Observation 2: When the uncertainty of product increases, the retailer should adapt more lenient fuzzy return.

In Figure 4.5, we simulate a special case from Figure 4.4(a) to illustrate the rate of optimal return policy. We use the same horizontal axis as in Figure 4.4 here, which is the uncertainty of the product. We pick two learning rates and plot the optimal return policy, which is q^*. The vertical axis in Figure 4.5 is the optimal return policy strategy, q^* and the scale is from 0 to 1. If the $q^* = 0$, indicates that Retailer should set up short return policy in stage 1, which means Retailer accepts no return after regular return stage. If $q^* = 1$, it means the

Retailer should set up long return policy in stage 1, which indicates the Retailer accepts all return after regular return stage. Any q^* in between, which is $0 < q^* < 1$, it indicates that Retailer accepts proportion of return when the product is returned after the regular return stage. The higher the q^* is, the higher acceptance rate for the fuzzy return is set up by the Retailer. In Figure 4.5, the dash line represents the change of q^* with high learning rate. The dotted line represents the change of q^* with low learning rate.

Figure 4.5: Optimal Return Policy for High/Low Learning



From Figure 4.5, we observe that the return policy starts from 0 and then slowly increases after a certain point for both learning rates. As the increase of the product uncertainty, consumers have more variance in product value. Retailer should offer more and more fuzzy return policy in order to improve sales if the uncertainty of the product increases.

The second observation we have in Figure 4.5 is that Retailer never offers a long return policy. In neither dash line nor dotted line, we never see any line that reaches to the point when $q^* = 1$. This indicates that, for neither high learning nor low learning customers, regardless of uncertainty of the product, Retailer should never offer long return. We also simulate the same graph for discount price product, and they all provide the same observation. The intuition behind this observation is that, if the Retailer offers a long return and accepts all return after the regular return stage, consumers will all keep the product and wait to return in the stage 4. This is harming the Retailer profit.

The last observation we have in this Figure is the difference in the degree of fuzzy return policy between different learning rates. Comparing dash line and dotted line, they do not have the same transition point from short return to fuzzy return. And both lines do not increase to the same degree of fuzzy return. This indicates that, for the same product, the Retailer should not have the same return policy for consumers with different learning rates. Consumers with a high learning rate should be offered a lower level of fuzzy return, meaning that Retailer should have a lower rate to accept return after the regular return stage for these consumers. The intuition behind this observation is that, when consumers have higher learning, they can pick up a more precise value of the product during the regular return stage. Hence, less fuzzy return from the Retailer.

4.4.2 Signaling Effect Model Result

In this section, we analyze signaling effect model. We solve the game theory prediction for the signaling effect model and listed the following propositions. The detailed solving process and proof can be found in Appendix B.

Proposition 2a: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, if the conditions satisfy in equation (4.10) *and*

(4.11), *the optimal fuzzy return policy is to offer long return, meaning that* $q^* = 1$.

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} < 0 \tag{4.10}$$

$$\pi^{1.2R}_{Retailer}(q=0) < \pi^{1.2R}_{Retailer}(q=1) \tag{4.11}$$

Proposition 2b: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, *if the conditions satisfy in equation* (4.12) *and* (4.13), *the optimal fuzzy return policy is to offer long return, meaning that* $q^* = 1$.

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} > 0 \tag{4.12}$$

$$\pi^{1.2R}_{Retailer}(q=q^*) < \pi^{1.2R}_{Retailer}(q=1) \tag{4.13}$$

Proposition 2c: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, *if the conditions satisfy in equation* (4.14) *and* (4.15), *the optimal fuzzy return policy is to offer short return, meaning that* $q^* = 0$.

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} < 0 \tag{4.14}$$

$$\pi^{1.2R}_{Retailer}(q=0) > \pi^{1.2R}_{Retailer}(q=1) \tag{4.15}$$

Proposition 2d: when the price of product is less than the mean of distribution for consumer value of the product, which is $p < \mu_0$, *if the conditions satisfy in equation* (4.16) *and*

(4.17), *the optimal fuzzy return policy is to offer fuzzy return, meaning that* $0 < q^* < 1$.

$$\frac{d\pi^{1.2R}_{Retailer}(q=0)}{dq} > 0 \tag{4.16}$$

$$\pi^{1.2R}_{Retailer}(q=q^*) > \pi^{1.2R}_{Retailer}(q=1) \tag{4.17}$$

Proof:

In this section, we calculate two conditions, the first condition is the derivative of the Retailer profit $\pi_{Retailer}$ at $q = 0$, listed in equation (4.9) . And the second set of condition is the difference between the Retailer profit of optimal return policy, q^*, and the Retailer profit of long return with signaling effect, $q = 1$.

In the second set of condition, we calculate the Retailer profit of optimal return policy, q^*, and the Retailer profit of long return with signaling effect, $q = 1$.

The Retailer profit of optimal return policy, q^*, is listed in the equation (4.18). The Retailer profit of long return with signaling effect is listed in equation (4.19).

$$\begin{aligned} \pi_{Retailer}(q=q^*) =& (-w)\int_{-\infty}^{s^*} g(s)\,ds + (q^*(-w) + (1-q^*)(p-w))\int_{s^*}^{\infty} F(p)\,g(s)\,ds \\ &+ (p-w)\int_{s^*}^{\infty}(1-F(p))\,g(s)\,ds \end{aligned} \tag{4.18}$$

$$\pi_{Retailer}(q=1) = (p)\int_{-\infty}^{\infty}(1-F(p))h(s)\,ds - w \tag{4.19}$$

We calculate the profit difference between the above two profits, listed in equation (4.20). If the difference is negative, it indicates that the profit of Retailer is higher when adopting a long return policy. If the difference is positive, the profit of Retailer is lower when adopting a long return policy.

$$diff = \pi_{Retailer}(q = q^*) - \pi_{Retailer}(q = 1) \tag{4.20}$$

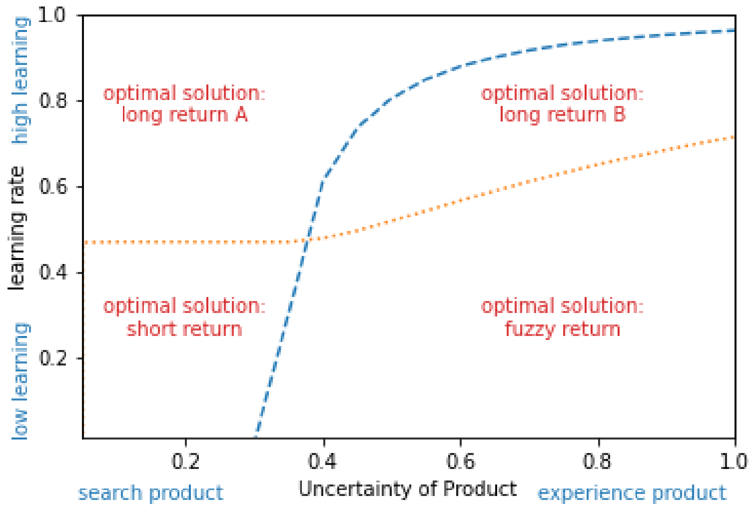
Combine two set of conditions and the Result 1, we can see that, if the derivative of Retailer profit over q at $q = 0$ is negative and the profit difference is negative, it indicates that the optimal return policy is long return, $q^* = 1$. If the derivative is negative and the profit difference is positive, the optimal return policy is short return, $q^* = 0$. If the derivative is positive and the profit difference is negative, the optimal return policy is long return, $q^* = 1$. If the derivative is positive and the profit difference is positive, the optimal return policy is fuzzy return, $0 < q^* < 1$.

4.4.2.1 Observation 3: In the signaling effect model, Retailer adopts a long return policy when the learning rate is high.

To demonstrate the result, we simulate the strategy mapping with signaling effect. Using the same set of value in Result 1, we add the signal, $\mu_1 = 1.1$, to the model. The signaling effect is that, when Retailer offers a long return policy, $q = 1$, the value distribution of the consumer follows $H \sim N(\mu_1, \sigma_0)$.

Figure 4.6 shows strategy mapping for the Retailer with signaling effect for regular price product. The horizontal axis is the uncertainty of product and the vertical axis is the learning rate. The dash and dotted line separates the graph into four areas. In the long return A area, the optimal return policy for the Retailer is to adopt a long return. In this area, the solution satisfies the condition in Proposition 2a. In the long return B area, the optimal return policy for the Retailer is to adopt a long return. In this area, the solution satisfies the condition in Proposition 2b.In short return area, the optimal return policy for the Retailer is to adopt a short return and in this area, the solution satisfies the condition in Proposition 2c. In the fuzzy return area, the optimal return policy for the Retailer is to adopt a fuzzy return. In this area, the solution satisfies the condition in Proposition 2d.

Figure 4.6: Strategy Mapping with Signaling Effect for Regular Price Product



In the Figure 4.6, we observe that, in the left side part from the dash line, is the situation when the derivative of Retailer profit over q is negative in Result 1. By adding the signaling effect into the model, we observe that there is an additional layer separating the left part by the dotted line. When the uncertainty of product is low, if the learning rate is high, which is in the upper left part of the graph, the optimal return policy for the Retailer is to adopt a long return. Under the same rate of product uncertainty, if the learning rate is low, the optimal return policy for the Retailer is to adopt a short return. These indicate that, when the uncertainty of the product is low, if the consumer has higher ability to resolve the uncertainty, the Retailer should accept all return outside the regular return stage. On the other hand, if the consumer has a lower ability to resolve the uncertainty of the product, the Retailer should accept no return outside the regular return stage. In the right side part from the dash line in Figure 4.6, is the situation when the derivative of Retailer profit over q is positive in Result 1. After adding the signaling effect into the model, we add an additional layer to the model, which is separated by the dotted line. In the upper right area of the graph is the situation when the uncertainty of the product is high and the learning rate is also high. In this situation, the optimal return policy for the Retailer is to adopt a long return. In the lower right area of the graph is the situation when the uncertainty of the product is high and the learning is low. In this situation, the optimal return policy for the Retailer is to adopt a fuzzy return. These indicate that, when the uncertainty of product is high, if the consumer has higher ability to resolve the uncertainty, the Retailer should accept all the return from the consumer outside the regular return stage. And for the same type of product, if the consumer has lower ability to resolve the product uncertainty, the Retailer should accept partial return outside the regular return stage. The intuition behind this observation is that, after we add the signaling effect to the base model, the signaling effect only changes the solution when the learning rate is high. This is intuitive. When the consumer has higher ability to resolve product uncertainty, it results in a narrower posterior distribution of consumer value. In that case, the signaling effect is stronger, since it has a higher expected value of the consumer value distribution.

In this section, we simulate several graphs to demonstrate the implication of our model. We find that, depending on the characteristics of the product (σ_0) and consumer type (σ_e), Retailer should choose between offering a short return policy or a fuzzy return policy. Retailer should also change the return policy when facing consumers with different learning rates. In the signaling effect model, Retailer should choose between offering a short return, a fuzzy return or a long return policy based on the uncertainty of the product and consumer learning rate.

4.5 Conclusion

This study investigates how we can incentivize the retailer to design their optimal return policy during the fuzzy return stage through the lens of game theory. We are among the first to shed light on the importance of fuzzy return, employing a combination of game theory and numerical analyses.

We have two main findings. First, we find that the Retailer needs to adopt different strategies during a fuzzy return stage depending on different levels of product uncertainty and different speed, at which consumers resolve the uncertainty. When the product uncertainty is low, the retailer should use a short return during the fuzzy return stage. Conversely, when the product uncertainty is high and consumers have low ability to resolve the uncertainty, the retailer should offer a fuzzy return during the fuzzy return stage. In the situation where the retailer should offer the fuzzy return, the rate of fuzzy return is increasing as the product uncertainty increases.

Second, by adding an additional layer of product value to the base model, we build the signaling effect model. We find that in the signaling effect model, Retailer should offer four different strategies. When the consumer learning rate is high, for both search product and experience product, Retailer should offer a long return. When the consumer learning rate is low, Retailer should offer a short return for the search product and a fuzzy return for the experience product.

This study also makes methodological contributions. It introduces a methodological framework to utilize game theory and numerical analysis to the context of fuzzy return and to study consumer return policy. Our study explores the flexibility that the retailer should offer when dealing with "non-standard" returns. Our findings suggest that the retailer should use different strategies for different products and when facing different consumer crowds.

From a managerial and return policy-making perspective, this study provides evidence that the level of fuzzy return should not be one-fits-all. If the retailer has multiple different products, they should offer different levels of return policy respectively.

The study is not without limitations. As one of the first studies to examine fuzzy return policy via game theory approach, we opt for a simple design in order to focus on the main interactions between the retailer and the consumers. Hence, some factors in real world scenarios are not fully explored. For example, we assume a complete information game where all the relevant parameters such as product values and the fuzzy return policy of retailer are known to all players when substantial asymmetric information may exist in reality. Another example is that we only consider the product that has a lower price than the mean of consumer value distribution in the model where in practice this is not always true.

The limitation of the study leads to potential future study alone in three directions. The first is to investigate how asymmetric information impacts the strategic interactions of the retailer and the consumers. The second is to extend the current model to cover different price ranges. Finally, a survey or an experiment can provide links between our theoretical results and real-world practices.

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4.7 Chapter 4 Appendix

4.7.1 Chapter 4 Appendix A Proof for Base Model

4.7.1.1 List of Variables

In Table 4.1, we list all our exogenous and endogenous variables.

Table 4.1: List of Variables

Exogenous variables:	
μ_0	mean of distribution for consumer value of the product
σ_0	standard deviation of distribution for consumer's value of the product. A low σ_0 means the product type is "search product" and a high σ_0 means the product type is an experience product.
σ_e	standard deviation of signal that consumer receives in the stage 4
p	price per unit of product
w	wholesale price per unit of product
c	cost of purchasing the product for consumer
$l = 1 - \frac{\sigma_e^2}{\sigma_0^2}$	learning rate, level of consumer ability to resolve the uncertainty of the product within the regular return stage. A high l means the consumer can highly resolve the uncertainty of the product within regular return stage. A low l means consumers has low ability to resolve the uncertainty of the product within the regular return stage
Endogenous variables:	
q	probability that retailer accept the fuzzy return after regular return stage, $q \in [0, 1]$. $q = 0$ means the retailer accepts no return request after regular return stage, all returns are short return.$0 < q < 1$ means the retailer offers accept some return request after regular return stage. $q = 1$ means the retailer accept all return request after regular return stage, all returns are long return

4.7.1.2 Calculation and Proof

Using the backward induction, we start by calculating the consumer utility in stage 2 with the following reason. Firstly, the uncertainty of the product only exists in the consumers model, which is after consumers purchase the product. There is no uncertainty in Retailer model. Secondly, by calculating the utility of the consumer, we would be able to determine the split of different branches, including regular return in Node (Regular Return), keep product in Node (Keep 2) and fuzzy return in Node (Fuzzy Return). Using the branches split determined by the consumer, we can calculate the split of retailer profit from different branches.

We start with finding the cut point between Node (Keep 2) and Node (Fuzzy Return). In stage 4, the consumer gets the realized product value v and will make the decision of keeping the product or proceeding to a fuzzy return. The utility of keeping the product is $v - p$ and the utility for fuzzy return is $q(0) + (1 - q)(v - p)$. Here the v is the realized product value and p is the product price. q is the degree of fuzzy return, which is measured as the probability that the Retailer would accept the fuzzy return. In stage 4, after observing the realized product value v, the consumer will keep the product if condition (4.21) is satisfied.

$$v - p > q(0) + (1 - q)(v - p) \tag{4.21}$$

Solve (4.21), we find that if $v > p$, the consumer will choose to keep the product, which will end up in Node (Keep 2) in stage 4. If $v < p$, the consumer will choose to return the product with fuzzy return, which will end up in Node (Fuzzy Return).

Using backward induction, we will be able to calculate the expected utility of consumer at stage 3 and it is shown in equation (4.22).

$$\begin{aligned} E(U^{Keep1}_{Comsumer}(q,\sigma_0,\sigma_v,p)) &= \int_{-\infty}^{p} (q(0)+(1-q)(v-p))\, f(v)\, dv + \int_{p}^{\infty} (v-p)\, f(v)\, dv \\ &= E(v) - p - q\int_{-\infty}^{p} (v)\, f(v)\, dv + q\cdot p \cdot F(p) \end{aligned} \tag{4.22}$$

Where $U^{Kepp1}_{Comsumer}(q,\sigma_0,\sigma_v,p)$ is the expected utility of consumer at stage 3 in Node (Keep 1). $f(v)$ is the probability density function of posterior distribution of product value that consumer has in stage 3. $F(p)$ is the cumulative density function of posterior distribution of product value at point p. $E(v)$ is the expected value of posterior distribution of product value.

At stage 3, the consumer will choose to keep the product, which is proceeds through Node (Keep 1) into stage 4 if the expected utility of consumer at stage 3 is greater than the utility consumer receives from regular return at Node (Regular Return). If the condition in (4.23) is satisfied, the consumer will choose to keep the product at stage 3.

$$E(v) - p - q\int_{-\infty}^{p} (v)\, f(v)\, dv + q\cdot p\cdot F(p) > 0 \tag{4.23}$$

Since $E(v)$, $f(v)$ and $F(p)$ all depends on the signal consumer receives at stage 3, we can simplified the condition in (4.23) to be a condition with a function of s^* in (4.24).

$$m - p - q\left(m - \sigma_v \frac{z(t)}{Z(t)}\right)\cdot F(p) + q\cdot p\cdot F(p) > 0 \tag{4.24}$$

Where $m = E(v) = \frac{\sigma_e^2}{\sigma_0^2+\sigma_e^2}\mu_0 + \frac{\sigma_0^2}{\sigma_0^2+\sigma_e^2}s$, $\sigma_v^2 = \frac{\sigma_0^2\sigma_v^2}{\sigma_0^2+\sigma_e^2}$, $m - \sigma_v\frac{z(t)}{Z(t)} = \int_{-\infty}^{p}(v)\, f(v)\, dv$ and $t = \frac{p-m}{\sigma_v}$. $z(t)$ and $Z(t)$ are the probability density function and cumulative density function of standard normal Z distribution for $t = \frac{p-m}{\sigma_v}$.

We define a $s^*(q,\sigma_0,\sigma_v,p)$, which sets a threshold of the signal that consumer receives in stage 3. If the signal that consumer receives, s_c, is greater than the $s^*(q,\sigma_0,\sigma_v,p)$, $s_c >$

$s^*(q, \sigma_0, \sigma_v, p)$, condition (4.24) is satisfied and consumer will choose to keep the product at stage 3. If consumer receives signal $s_c < s^*(q, \sigma_0, \sigma_v, p)$, condition (4.24) is unsatisfied and consumer will choose to return the product at stage 3.

Until here, we find the proportion of consumers that goes into three branches of decisions in the model if they choose to purchase. After purchases the product, consumer will receive a random signal drawn from the prior distribution, g. If this signal is less than the $s^*(q, \sigma_0, \sigma_v, p)$, consumer will proceed to regular return and gain the utility of 0. If the signal is greater than the $s^*(q, \sigma_0, \sigma_v, p)$, the consumer will continue keep the product until they are in stage 4, in which they receive a firm value, v, of the product. After that, if the product value, v, is greater than the product price, p, the consumer will keep the product and gain the utility of $v - p$. Otherwise, if $v < p$, the consumer will proceed to a fuzzy return and gain the utility of $q(0) + (1 - q)(v - p)$.

Retailer receives the profit differently from three branches. The first branch is the proportion of consumers who return within the regular return stage at stage 3 in Node (Regular Return). Retailer receives $-w$ from consumers that do regular return and the proportion of consumers that do regular return is $\int_{-\infty}^{s^*(q,\sigma_0,\sigma_v,p)} g(s)\, ds$. This part of consumers receives signal less than $s^*(q, \sigma_0, \sigma_v, p)$ at stage 3. If consumers choose the keep the product at the end, which is in Node (Keep 2), Retailer receives the profit of $p - w$. p is the product price and w is the wholesale price, which is the cost for Retailer. The proportion of consumers in this branch is $\int_{s^*(q,\sigma_0,\sigma_v,p)}^{\infty} (1 - F(p))\, g(s)\, ds$, which represents consumers who receive the signal higher than $s^*(q, \sigma_0, \sigma_v, p)$ at stage 3 and also gets the realized product value v greater than p at stage 4. If consumers choose to proceed to fuzzy return at stage 4, which is in Node (Fuzzy Return), Retailer receives the profit of $q(-w) + (1 - q)(p - w)$.The proportion of consumers in this branch is $\int_{s^*(q,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)\, ds$. This includes the consumers, who receives the signal higher than $s^*(q, \sigma_0, \sigma_v, p)$ at stage 3 and gets the realized v less than p at stage 4.

Combining the proportions and profit, we calculate the total profit of Retailer and it is shown in equation (4.25).

$$
\begin{aligned}
\pi_{Retailer}(q) =&(-w)\int_{-\infty}^{s^*(q,\sigma_0,\sigma_v,p)} g(s)\, ds+ \\
&+ (q(-w) + (1-q)(p-w)) \int_{s^*(q,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)\, ds \\
&+ (p-w)\int_{s^*(q,\sigma_0,\sigma_v,p)}^{\infty} (1-F(p))\, g(s)\, ds
\end{aligned}
\tag{4.25}
$$

We then find the optimal strategy for fuzzy return policy, q, by taking the derivative of the profit of Retailer, $\pi^{1.2R}_{Retailer}(q)$, over q.

$$
\begin{gathered}
\frac{d\pi_{Retailer}(q)}{dq} = \\
(-w)g(s^*(q,\sigma_0,\sigma_v,p))\frac{ds^*(q,\sigma_0,\sigma_v,p)}{dq} + (-w+(-1)(p-w))\int_{s^*(q,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)ds \\
+(q(-w)+(1-q)(p-w))\,(-F(s^*(q,\sigma_0,\sigma_v,p)))\cdot g(s^*(q,\sigma_0,\sigma_v,p))\,\frac{ds^*(q,\sigma_0,\sigma_v,p)}{dq} \\
+(p-w)\left(-g(s^*(q,\sigma_0,\sigma_v,p))\frac{ds^*(q,\sigma_0,\sigma_v,p)}{dq}\right) \\
+(p-w)\left(F(s^*(q,\sigma_0,\sigma_v,p))\cdot g(s^*(q,\sigma_0,\sigma_v,p))\frac{ds^*(q,\sigma_0,\sigma_v,p)}{dq}\right)
\end{gathered}
\tag{4.26}
$$

In order to find out if the model has interior solution or corner solution, we evaluate the derivative in equation (4.26) at two end points of q, which are $q = 0$ and $q = 1$.

We start with the derivative evaluation when $q = 0$. When $q = 0$, the $s^*(q = 0, \sigma_0, \sigma_v, p)$ is calculated using the equation (4.27) and can be solved equal to equation (4.28). Derivative of $\pi_{Retailer}(q=0)$ over q can be calculated using equation (4.29).

$$m - p = \frac{\sigma_e^2}{\sigma_0^2+\sigma_e^2}\mu_0 + \frac{\sigma_0^2}{\sigma_0^2+\sigma_e^2}s^*(q,\sigma_0,\sigma_v,p) - p = 0 \tag{4.27}$$

$$s^*(q=0,\sigma_0,\sigma_v,p) = \frac{\beta}{\beta_e}p - \frac{\beta_0}{\beta_e}\mu_0 \tag{4.28}$$

$$\begin{aligned} &\frac{d\pi_{Retailer}(q=0)}{dq} \\ &= -p\cdot g(s^*(q=0,\sigma_0,\sigma_v,p))\frac{ds^*(q=0,\sigma_0,\sigma_v,p)}{dq} + (-p)\int_{s^*(q=0,\sigma_0,\sigma_v,p)}^{\infty} F(p)\,g(s)\,ds \\ &= -p\cdot g(\frac{\beta}{\beta_e}p - \frac{\beta_0}{\beta_e}\mu_0)\frac{ds^*(q=0,\sigma_0,\sigma_v,p)}{dq} + (-p)\int_{\frac{\beta}{\beta_e}p-\frac{\beta_0}{\beta_e}\mu_0}^{\infty} F(p)\,g(s)\,ds \end{aligned} \tag{4.29}$$

Where $\frac{1}{\beta_0} = \sigma_0^2$, $\frac{1}{\beta_e} = \sigma_e^2$ and $\beta = \beta_0 + \beta_e$. $\frac{ds^*(q=0,\sigma_0,\sigma_v,p)}{dq}$ is shown in equation (4.30).

$$\begin{aligned} &\frac{ds^*(q=0,\sigma_0,\sigma_v,p)}{dq} \\ &\frac{\frac{\beta_0}{\beta}\mu_0\cdot F(p) + \frac{\beta_e}{\beta}s\cdot F(p) - \frac{1}{\sqrt{\beta}}z(t) - p\cdot F(p)}{\frac{\beta_e}{\beta} - q\cdot\frac{\beta_0}{\beta}\mu_0\cdot\frac{\partial F(p)}{\partial s} - q\cdot\frac{\beta_e}{\beta}s\cdot\frac{\partial F(p)}{\partial s} - q\cdot\frac{\beta_e}{\beta}\cdot F(p) + q\cdot\frac{1}{\sqrt{\beta}}\frac{\partial z(t)}{\partial s} + q\cdot p\cdot\frac{\partial F(p)}{\partial s}} \end{aligned} \tag{4.30}$$

Derivative of $\pi_{Retailer}(q=0)$ over q can be simplified to equation (4.31).

$$\frac{d\pi_{Retailer}(q=0)}{dq} = p\cdot g(\frac{\beta}{\beta_e}p - \frac{\beta_0}{\beta_e}\mu_0)\left(\frac{\sqrt{\beta}z(t)}{\beta_e}\right) + (-p)\int_{\frac{\beta}{\beta_e}p-\frac{\beta_0}{\beta_e}\mu_0}^{\infty} F(p)\,g(s)\,ds \tag{4.31}$$

Since the Retailer profit is a continuous function, if $\frac{d\pi_{Retailer}(q=0)}{dq}$ is positive, it indicates that the Retailer profit, $\pi_{Retailer}(q)$, is increasing at $q=0$. If the derivative is negative, it indicates that the Retailer profit is decreasing at $q=1$. We listed these two conditions in equation (4.32) and equation (4.33).

$$p\cdot g(\frac{\beta}{\beta_e}p - \frac{\beta_0}{\beta_e}\mu_0)\left(\frac{\sqrt{\beta}z(t)}{\beta_e}\right) + (-p)\int_{\frac{\beta}{\beta_e}p-\frac{\beta_0}{\beta_e}\mu_0}^{\infty} F(p)\,g(s)\,ds > 0 \tag{4.32}$$

$$p \cdot g(\frac{\beta}{\beta_e}p - \frac{\beta_0}{\beta_e}\mu_0)\left(\frac{\sqrt{\beta}z(t)}{\beta_e}\right) + (-p)\int_{\frac{\beta}{\beta_e}p-\frac{\beta_0}{\beta_e}\mu_0}^{\infty} F(p)\, g(s)\, ds < 0 \tag{4.33}$$

We then evaluate the derivative of $\pi_{Retailer}(q)$ at another end point of $q = 1$. Given $q = 1$, $s^*(q = 1, \sigma_0, \sigma_v, p)$ is calculated using the equation (4.34). The solution is $s^*(q = 1, \sigma_0, \sigma_v, p) = -\infty$, and it indicates that for any $s^*(q = 1, \sigma_0, \sigma_v, p)$, $E(U^{Keep1}_{Consumer}(q = 1, \sigma_0, \sigma_v, p))$ is always greater than 0. Condition (4.24) is always satisfied when $q = 1$. This is intuitive. Since when $q = 1$, there is no difference for utility of consumer between regular return in Node (Regular Return) and fuzzy return in Node (Fuzzy Return). Hence consumers should always choose to keep the product in Node (Keep 1) and take some extra time to evaluate the product until the product value is realized.

$$\begin{aligned} & m - p - \left(m - \sigma_v \frac{z(t)}{Z(t)}\right) \cdot F(p) + \cdot p \cdot F(p) \\ = & \left(\frac{\beta_0}{\beta}\mu_0 + \frac{\beta_e}{\beta}s - p\right)(1 - \frac{1}{2}\left(1 + erf\left(\frac{\beta_0(p-\mu_0) + \beta_e(p-s)}{\sqrt{2}\sqrt{\beta}}\right)\right)) \\ & + \frac{1}{\sqrt{\beta}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{\beta_e^2(\mu_0 - s)^2}{\beta}\right)\right\} \\ & = 0 \end{aligned} \tag{4.34}$$

We then find the derivative, $\frac{d\pi_{Retailer}(q=1)}{dq}$ and it is listed in equation (4.35).

$$\begin{aligned}
&\frac{d\pi_{Retailer}(q=1)}{dq} \\
&= -p \cdot g(s^*(q=1,\sigma_0,\sigma_v,p))\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \\
&+F(s^*(q=1,\sigma_0,\sigma_v,p)) \cdot g(s^*(q=1,\sigma_0,\sigma_v,p))\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \cdot p \\
&+(-p)\int_{s^*(q=1,\sigma_0,\sigma_v,p)}^{\infty} F(p)\, g(s)\, ds \\
&= -p \cdot g(-\infty)\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \\
&+F(-\infty) \cdot g(-\infty)\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} \cdot p + (-p)\int_{-\infty}^{\infty} F(p)\, g(s)\, ds
\end{aligned} \tag{4.35}$$

Where

$$\frac{ds^*(q=1,\sigma_0,\sigma_v,p)}{dq} = \frac{F(p)\left(\frac{\beta_0}{\beta}\mu_0 + \frac{\beta_e}{\beta}s^*(q=1,\sigma_0,\sigma_v,p) - p\right) - \frac{1}{\sqrt{\beta}}\frac{1}{2\pi}\exp\left\{-\frac{1}{2}\left(\frac{(\beta_0(p-\mu_0)+\beta_e(p-s^*(q=1,\sigma_0,\sigma_v,p)))^2}{\beta}\right)\right\}}{\frac{\beta_e}{\beta} + \frac{\partial F(p)}{\partial s}(-\frac{\beta_0}{\beta}\mu_0 - \frac{\beta_e}{\beta}s^*(q=1,\sigma_0,\sigma_v,p) + p) - \frac{\beta_e}{\beta} \cdot F(p) + \frac{1}{\sqrt{\beta}}\frac{\partial z(t)}{\partial s}} \tag{4.36}$$

The derivative $\frac{d\pi_{Retailer}(q=1)}{dq}$ is always negative. This indicates the Retailer profit is always decreasing at $q = 1$.

$$\frac{d\pi_{Retailer}(q=1)}{dq} < 0 \tag{4.37}$$

From the derivative, we find that, if condition (4.32) and condition (4.37) are satisfied, this guarantees an interior solution of the model. It means the optimal solution is $0 < q^* < 1$. This indicates a fuzzy return which offers some probability of accepting the fuzzy return should be the optimal strategy for Retailer under this condition.

If condition (4.33) and condition (4.37) are satisfied, this guaranteed a corner solution for the model, which is $q^* = 0$. This indicates that, under this condition, Retailer should not accept any return after the regular return stage. Retailer should only offer a short return under this condition.

In this section, we show the complete solution process and proof to find the conditioned strategy for the return policy model.

4.7.2 Chapter 4 Appendix B Proof for Signaling Effect Model

In the signaling effect model, we add an extra layer to the base model. This extra layer is when the Retailer sets up the return policy to be a long return, consumers have a different value distribution for the product. That is when $q = 1$, the posterior value distribution for the product from consumer is $v_{prior|q=1} \sim N(\mu_1, \sigma_0^2)$, where $\mu_1 > \mu_0$. This indicates that when the Retailer sets the return policy to be long return, consumers have a positive signaling effect, which results in a higher expected value of product value distribution.

From previous proof of the base model, we learn that, depending on conditions in Proposition 1a and 1b, the optimal fuzzy return policy for the Retailer is either offer short return or fuzzy return. In the signaling effect model, we use these two conditions and compare the profit of the Retailer between the optimal return policy in the base model and the profit when the Retailer offers a long return.

In the first condition, which is in Proposition 1a, the optimal return policy set by the Retailer is short return, $q^* = 0$, in the base model. We compare the profit of the Retailer at $q = 0$ in the base model, $\pi_{Retailer}(q = 0)$, and the profit of the Retailer for long return with signaling effect, $\pi^{1.2R}_{Retailer}(q = 1)$. Two profits, $\pi_{Retailer}(q = 0)$ and $\pi_{Retailer}(q = 1)$ are given in the equation (4.38) and (4.39).

$$\begin{aligned}\pi_{Retailer}(q=0) &= (-w)\int_{-\infty}^{s^*} g(s)\,ds + (p-w)\int_{s^*}^{\infty} F(p)\,g(s)\,ds + (p-w)\int_{s^*}^{\infty}(1-F(p))\,g(s)\,ds \\ &= \frac{1}{2}p - w\end{aligned} \tag{4.38}$$

$$\pi_{Retailer}(q=1) = (p)\int_{-\infty}^{\infty}(1-F(p))h(s)\,ds - w \tag{4.39}$$

If $\pi_{Retailer}(q=0) > \pi_{Retailer}(q=1)$, it indicates that the profit of the Retailer is higher when adopting short return policy, that is the optimal return policy for the Retailer is to offer short return. If $\pi_{Retailer}(q=0) < \pi_{Retailer}(q=1)$, it indicates the profit of the Retailer is higher when adopting long return, that is the optimal return policy for the Retailer is to offer long return.

In the second condition, which is in Proposition 1b, in the base model, the optimal return policy set by the Retailer is fuzzy return, $0 < q^* < 1$. We compare the profit of the Retailer at $q = q^*$ in the base model, $\pi_{Retailer}(q = q^*)$ and the profit of the Retailer for the long return in signaling effect model, $\pi_{Retailer}(q=1)$. Two profits, $\pi_{Retailer}(q=q^*)$ and $\pi_{Retailer}(q=1)$ are given in the equation (4.40) and (4.41).

$$\begin{aligned}\pi_{Retailer}(q=q^*) =&(-w)\int_{-\infty}^{s^*} g(s)\,ds + (q^*(-w) + (1-q^*)(p-w))\int_{s^*}^{\infty} F(p)\,g(s)\,ds \\ &+ (p-w)\int_{s^*}^{\infty}(1-F(p))\,g(s)\,ds\end{aligned} \tag{4.40}$$

$$\pi_{Retailer}(q=1) = (p)\int_{-\infty}^{\infty}(1-F(p))h(s)\,ds - w \tag{4.41}$$

If $\pi_{Retailer}(q = q^*) > \pi_{Retailer}(q = 1)$, it indicates that the profit of the Retailer is higher when adopting the fuzzy return. This means the optimal return policy for the Retailer in the signaling effect model is to offer fuzzy return. If $\pi_{Retailer}(q = q^*) < \pi_{Retailer}(q = 1)$, it indicates that the profit of the Retailer is higher when adopting long return. In this case, the optimal return policy for the Retailer in the signaling effect model is to offer a long return.

From the above two conditions, we solve the signaling effect and get four optimal solutions, depending on different conditions and situations.

CHAPTER 5

General Conclusions

In this dissertation, we study the market power and the investment decision. Also, we investigate the problem of retailer setting up the fuzzy return policy.

In the "How Dominant Market Power Impacts OEM Investments in the Supply Chain - Theory and Experiment", we study the investment decision of OEM in a dual-channel supply chain setting. We investigate the investment decision of OEM under different market power situations. Using game theoretical analysis, we find the condition for the OEM to invest under different market power situations. We conduct the lab experiment to test the human decision with the above setting. From the experiment, we find that OEM has under-investment behavior when they should not invest and over-investment when they should invest. However, OEM learns to adjust towards game theory equilibrium as time goes. We also find that the investment decision of OEM responses to the market power, but not to the investment cost. When we take the perspective of the entire supply, both game theory equilibrium and experiment results show that the investment is beneficial to the centralized supply chain. Hence, we suggest using the investment as a way to increase channel efficiency.

In the "An Experimental Study of Market Power in the Dual-Channel Competition", we extend the previous study by adding the probability layer to the market power. We employ the same dual channel supply chain setting with one retailer and one supplier. Instead of using extreme market power options, we set the market power as the probability of the wholesale price being selected by the supply chain system. We also add more investment options, including investing in supplier production, retailer marketing and quality to the retailer. We calibrate two sets of parameters in the experiment. One is when investing in supplier production is the optimal investment decision and another is when investing in quality is the optimal investment decision. We also calibrate two sets of market power conditions, one is retailer power and another is supplier power. We conduct a lab experiment to observe the human decision with our hypothesis. We observe that retailer does not always follow the game theoretical prediction when choosing which option to invest. Furthermore, their investment option is partially affected by the market power, which is not predicted by the game theory model. We find similar results in the wholesale price decision set by both retailer and supplier. With these off-equilibrium behavior, we run the behavior model with a quantal response choice framework. With the behavior model, we find that the retailer are bounded rational when setting up the wholesale price. However, retailer are bounded rational on the investment option only when she has power. We conclude that retailer are bounded rational and her decisions are impacted by the market power.

In the "Design Optimal Fuzzy Return for Retailer", we study the retailer decision on the fuzzy return policy. The fuzzy return is defined as the return request from the consumer, which is outside the standard return policy but not completely unacceptable by the retailer. We build a game theory model with a retailer and a market of consumers. The retailer set up the fuzzy return policy, which is the probability to accept the fuzzy return. The consumer purchases the product and, depending on his/her value of the product, chooses to keep, regular return or fuzzy return the product. The consumer value of the product is randomly drawn from the value distribution, which is controlled by the product fit uncertainty and the ability of the consumer to resolve the uncertainty during usage. Using the game theory analysis, we solve the condition which separates the fuzzy return policy of retailer into two strategies. One is to offer a short return, which is to accept no return outside the regular return stage. Another is to offer a fuzzy return, which is to accept part of return outside the regular return stage. With model simulation, we observe the above theoretical prediction. We also observe that the degree of fuzzy return policy increases as the product fit uncertainty increases. On top of the above base model, we add the signaling effect to the base model. The signaling effect happens when the retailer offers a long return. Using game theory, we solve the condition that separates the retailer return policy into four strategies. Two are to offer a long return, one is to offer a short return and the last one is to offer a fuzzy return. We conclude that, depending on the product fit uncertainty and the ability of the consumer to resolve the uncertainty, the retailer should offer a different fuzzy return policy.

Biographical Information

Jingjie Su was born in Xiamen, China. She earned the BA degree, majored in English Language and Literature and minored in International Economics and Trade, from the Shanghai International Studies University. After that, she moved to the U.S. to pursue the MBA degree at the University of Texas at Arlington. In 2015, she joined the PhD program, concentrating in Management Sciences, in the University of Texas at Arlington. Her research interests are behavioral operations management, supply chain omni-channel, retailer return policy and applied game theory.