Pricing with Quality Perception: Theory and Experiment

by

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Abstract

Quality is one of the most important factors behind a decision to purchase any product. Consumers have long assumed that price and quality are highly correlated, and that as the price of a product increases, its quality also increases ("you get what you pay for"). Several researchers have studied how consumers use price to infer quality, but very few have investigated the impact of pricing strategies, particularly price markdowns, on quality perception and how a retailer should react to such behavior. Our key research questions, viewed through both an empirical and a theoretical lens, concern how markdowns with different discount levels may induce different consumer behaviors and how the firm should incorporate them when optimizing its markdown policy. We empirically elicit the relationship between a consumer's quality perception and available price information, and refine a consumer demand model to capture these insights, together with other motives—reference dependence, loss aversion, patience, and optimism. For the retailer, we characterize the structure of the market segmentation and analyze its optimal markdown strategy when consumers are sensitive to quality. We present conditions in which it is optimal for the firm to apply a markdown to its products. When consumers are more sensitive to the product's original price than to the discount, or are impatient to wait for the future discounts, the retailer can earn the maximum revenue when applying a markdown strategy. Furthermore, we advocate that the firm should pre-announce the information about future markdowns in order to avoid the negative effect of the consumers' inaccurate estimates.

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Chapter 1

Introduction

Three months before starting her first job out of college, Rey is looking for a new handbag she can bring to work. In the "New Arrival" section of her favorite store, a white leather handbag catches her eye and its price tag says $198.00. "The design is very nice. Almost $200 is certainly pricey," Rey thinks to herself, "but given the price, this bag will probably have a pretty good quality and can last a long time." Knowing that this store often marks down its products, Rey decides to wait for a potential markdown. Three months later, Rey comes back to the store and finds the same handbag still available. It is also on markdown: "Was: $198.00. Now: $79.99. 60% off". Examining the price tag, Rey thinks, "This seems like a great deal. But does the 60% off mean that this handbag is not as durable as I have expected?" Rey is contemplating the quality of the handbag and is a bit hesitant to buy it now.

For many customers, like Rey, important factors that trigger their purchase decision are not only prices, but also the product's quality (Moorman 2015). Customers may not have full knowledge about the quality before the actual use, but they can make a quality judgment from available information, such as price (Rao and Monroe 1988, 1989, Rao and Sieben 1992), discount (Gupta and Cooper 1992, Grewal et al. 1998, González et al. 2016), advertising effort (Kirmani and Wright 1989), and store/brand name and reputation (Shapiro 1983, Dodds et al. 1991, Grewal et al. 1998). In this thesis, we focus on the impact of price information, such as a product's original price and if a markdown is applied, the corresponding discount level and the product's final price. Such price information is salient when consumers make purchases. Several researchers have found that price is an efficient signal for product quality; higher prices imply higher quality (Biswas and Blair 1991, Lichtenstein and Burton 1989, Lichtenstein et al. 1991, Rao and Monroe 1988, 1989, Bagwell and Riordan 1991). Past studies suggest that the consumers' perception of product quality not only depends on the listed price itself, but may also depend on whether the price is the result of a discount (Orth and Krška 2001, Alford and Biswas 2002, Darke and Chung 2005). A few empirical studies have shown that discount prices can have positive effects on a consumer's perception of value (Compeau and Grewal 1998, Darke and Dahl 2003), while other studies have suggested that discounts lead to negative perception of the product quality (Raghubir and Corfman 1999). In what particular way does a complete price information affect quality perception? This is one of the questions this thesis intends to answer.

The increasing use of dynamic pricing tactics in retail has substantially influenced consumers' purchase behavior. Both practitioners and researchers are paying more attention to how consumers react to changes in pricing strategies. Common among many forms of price reductions, a markdown strategy is a permanent reduction of the initial retail price. Especially in the apparel industry, markdowns allow the retailer to sell off merchandise. Sales from markdowns have recently contributed more than 30% of total revenues in department and specialty stores in the United States, up from less than 10% in the 1970s (Zentes et al. 2007). As consumers anticipate significant price markdowns (Jacobson and Obermiller 1990, Gumpert and Cavale 2015), they may postpone their purchases in order to wait for the discount. However, not everyone wants to wait. While steep discounts are attractive to some consumers, at the same time they could send a negative signal about quality to others (Shell 2009). Consumers can also be more inclined to buy early in the season if they view a higher price as a signal of higher quality and want to enjoy the products earlier—"an instant gratification" (Stout 2013). Trading off between price and quality is a difficult task for consumers (Luce et al. 1999); they seek good deals to pay the cheapest price for a high-quality product. For retailers, understanding the consumers' quality perceptions and decision-making process enables them to choose an appropriate markdown strategy to capture the right demand and maximize their profit. This thesis aims to deepen the understanding of how consumer quality perception can impact the retailer's pricing strategy, particularly with regard to markdown pricing.

Our main research questions are: (i) How do consumers' perceived quality of a product (and hence their purchase decisions) depends on the listed original price, the discount level, and the final selling price? (ii) How should a retailer optimally choose among several possible discount levels in order to maximize revenue, given the induced quality perception among the consumers? In this thesis, we consider a setup in which a retailer sells a single product under a markdown strategy over two periods. Consumers arrive in both periods and form quality perceptions given the available price information. They decide whether and when to purchase the product, while the retailer takes into account the strategic consumers' purchase decisions and optimizes its markdown strategy. Our approach consists of two steps. In the first step, we design a consumer purchase experiment to empirically estimate and develop a functional relationship between the consumers' quality perceptions and available price information at the time of purchase. We then incorporate these experimental insights into a refined consumer behavior model, that allows us to characterize the retailer's optimal markdown strategy when quality perceptions are taken into account.

Our contributions are threefold. First, we study pricing in combination with quality perception using a methodology that integrates empirical examination with modeling analysis. In the marketing domain, researchers have empirically studied price-based quality perception (McConnell 1968, Peterson and Jolibert 1976, Wheatley and Chiu 1977, Darke and Chung 2005, Suk et al. 2012) and the connection between perceived quality and purchase intention (Taylor and Baker 1994, Chang and Wildt 1994). However, very few studies have investigate how multiple pieces of price information jointly influence quality perception (Hardesty and Bearden 2003, Darke and Chung 2005). In addition, to the best of our knowledge, we have not been able to find work that connects empirical studies of price-based quality perception into the modeling analysis of optimal pricing strategies. We fill this gap by grounding our analysis on the retailer's optimal markdown strategy in an empirically validated model of perceived quality. Within the operations management (OM) literature on pricing management, there has been a growing interest in developing more realistic consumer models and incorporating aspects of consumer behavior as a foundation for price optimization (Anderson and Wilson 2003, Su 2007, Aviv and Pazgal 2008, Cohen et al. 2014). We add to these efforts by capturing another important aspect in consumers' purchase decisions, i.e., quality perception induced by price information.

Second, we develop a more comprehensive consumer behavior model that captures a set of salient behavioral factors, particularly quality perception, reference-dependent preferences, loss aversion, patience, and optimism. Regarding quality perception, our experimental design allows us to systematically examine how consumers' perceived quality is affected by price information and their time of arrival to the market. We also investigate the sensitivity of these relationships with respect to demographics and product categories. These empirical findings offer valuable insights for translating our modeling results on comparative statics into practical implications. In addition, we further capture the consumers' gain/loss utilities associated with potential discrepancies between their expected discount and the realized discount in the markdown period. This comprehensive account of consumer behavior allows us to study how various factors jointly influence the consumers' purchase decisions as well as the resulting optimal strategy for a retailer who is cognizant of these behavioral factors. Our approach is in line with recent calls for advancing consumer research by studying the joint impacts of multiple salient behavioral factors (Narasimhan et al. 2005, Ho et al. 2006).

Lastly, we develop a model that could help the retailer gain a better understanding of the market segmentation and how to execute a markdown strategy optimally. By considering how consumers connect price information with quality perception, we fully characterize the demand of a product in both the initial sale and markdown periods. We determine when applying markdown is optimal for the retailer by examining the joint effects of consumersÕ price-induced quality perceptions, their optimism about and patience to wait for future markdown, and gain/loss feelings. Our analysis on comparative statics suggest conditions under which the retailer is encouraged to use markdown pricing depending on consumer behavior and product characteristics. In particular, markdowns are attractive to the firm when its consumers infer the product quality from the original price rather than the discount or are willing to purchase the product early in the season. Since the discrepancies between their expectations and the actual markdowns have a negative impact on the revenue, it is in the firm's best interest to communicate the information about future markdowns to its consumers prior to the markdown period in order to mitigate such impact.

The remainder of the thesis is organized as follows: Section 1.1 provides a review of the relevant literature. Section 1.2 introduces the research setup and methodology that give an overview of Chapters 2 and 3. The design, procedure and results of our consumer purchase experiment are presented in Chapter 2. Chapter 3 describes our analytical model, which characterizes the market segmentation and derives an optimal markdown strategy for the retailer. Finally, we conclude with numerical experiments and sensitivity analysis of model parameters in Chapter 4, and managerial implications of our results in Chapter 5.

1.1 Literature Review

Our work is related to three streams of prior literature in pricing. First, there is a large body of work that studies how forward-looking consumer behavior affects a firm's operational decisions. We contribute to a growing field of behavioral operations management, which has extensively examined behavioral regularities and their impacts on the firm's pricing strategies, by deepening the analysis of quality perception in a pricing context. Lastly, marketing researchers have long studied how prices may be used by consumers as a signal of product quality. One of our primary goals in this thesis is to bridge these pieces of work through both an empirical and analytical approach that allows us to model both the behavior of strategic consumers but also the retailer's optimization problem when price and quality perception are key factors behind purchase decisions.

In the past few decades, researchers in the area of pricing have extensively studied consumers' strategic behavior and their implications in the retailer's optimal pricing strategy (Erdem and Keane 1996, Hendel and Nevo 2006, Nair 2007). Strategic consumers are forward-looking in the sense that they strategically time their purchases, and they have been observed in a variety of settings. For example, Chevalier and Goolsbee (2009) empirically show that forward-looking textbook buyers anticipated book revisions before making their purchase decisions, while Li et al. (2014) reveal that airline passengers strategically choose between either booking their tickets at the beginning of the booking horizon or close to departure. Strategic behaviors potentially affect the firm's operational decisions (see Shen and Su (2007) and Netessine and Tang (2009) for a comprehensive review) such as the impact of stockpiling on the planning of promotions in grocery retail (Cohen et al. 2014). However, the impact has been found to vary depending on the market (Li et al. 2014). While some believe that strategic consumers have a negative impact on the firms' profits (Anderson and Wilson 2003, Aviv and Pazgal 2008, Levina et al. 2009), others argue that it could be positive for some product categories or some price ranges (Su 2007, Cho et al. 2009). As a response to forward-looking behavior, the firm needs to optimally choose different prices over multiple periods in order to capture the highest profit from different types of customers. Talluri and van Ryzin (2006) provide a thorough overview of the value of price discrimination and capacity allocation based on consumers' heterogenous valuations of a good or service. Several researchers have studied intertemporal pricing, including markup and markdown policies, and its connection with strategic consumer behaviors (Su 2007, Besbes and Lobel 2015, Chen and Farias 2015). Our focus is similar to that of recent researchers who restrict attention to markdown pricing mechanisms (Elmaghraby et al. 2008, Harsha et al. 2011, Özer and Zheng 2015). The main way we differ from Elmaghraby et al. (2008) is our assumption that the consumers' valuations of products are not publicly known and the level of markdown is not pre-announced. Harsha et al. (2011) also investigate behavioral issues around consumers who return to buy a product after observing past sales in a fashion retailer, but our work extends to various types of fashion and hi-tech products, and we also incorporate more behavioral aspects. Lastly, we study the role of quality perception in markdown management in a similar manner as Özer and Zheng (2015) study regret and availability misperception, but we use the consumer purchase experiments in addition to modeling analysis to gain further insights into strategic consumer behavior.

Recently in operations and marketing settings, there is growing attention on the impact of behavioral regularities on pricing. Loss aversion, reference-dependent preferences, and regret are among the popular behavioral issues found to induce behavioral anomalies in a variety of contexts. Under these systematic concepts, consumers may perceive losses, relative to some reference point, as being more significant than gains of the same objective magnitude. In the context of pricing, loss aversion and reference dependence imply that demand would be sensitive to previous pricing strategies consumers may have seen. For example, consumers are more likely to buy a product whose historical prices were high than if they were previously low. Özer and Phillips (2012) provide a comprehensive review of how different behavioral motives affect the firm's marketing and pricing decisions. The model of reference-dependent preferences developed by Kőszegi and Rabin (2006) introduces a "gain-loss utility" as an addition to a standard consumption utility to reflect the consumers' feelings of gain or loss when observing an outcome different than their expectations. For performing arts and concerts, Tereyagoglu et al. (2014) show that the consumers suffer utility loss when the ticket prices are above their references or when the actual seat sales do not perform as well as they expected. Researchers have recently moved towards the development of how the firm should make price decisions given behavioral regularities (Popescu and Wu 2007, Heidhues and Kőszegi 2008, Nasiry and Popescu 2011, Baron et al. 2015). We extend this framework to model how consumers form a reference point for a future discount and how they react to the realized markdown when visiting the store for a second time. To the best of our knowledge, we are among the first to extensively study the formation of quality perception from price information and connect it with other behavioral aspects, including optimism and patience.

Quality has been regarded as one of the important factors that determine consumers' satisfaction with a product. While a manufacturer may have complete knowledge of its product's quality, making a quality judgment can be difficult for consumers, especially before the actual product consumption. Researchers have looked into how available cues, such as price, brand image, and store name, can signal the product quality (Hoch and Deighton 1989, Janiszewski and Van Osselaer 2000, Waber et al. 2008). Sale prices are considered as an important marketing cue (Biswas and Blair 1991, Lichtenstein et al. 1991, Thomas and Morwitz 2009) and a reasonably good indicator of quality for consumers (Rao and Monroe 1988, Rao and Sieben 1992). The earliest stream of research around the relationship between price and quality dates from 1949 when Knauth (1949) observed positive sales response following a price increase and concluded that a higher price suggested higher value. Since then, additional studies have shown that consumers frequently use price as a signal for product quality (Gabor and Granger 1966, Stafford and Enis 1969, Monroe 1973, Rao and Monroe 1989). Due to the low correlation between price and actual product quality (Tellis and Wernerfelt 1987), it has been a challenge to elicit a relationship that could approximate data well. While Lichtenstein and Burton (1989) and Caves and Greene (1996) observe a strong positive price-quality relationship for nondurables and frequently purchased products, Gerstner (1985) finds that hot-air corn poppers with higher prices could have lower objective quality than those of lower prices. For a review of the price-quality relationship, see Völckner and Hofmann (2007) and Kardes et al. (2008). Our research further investigates the impact of price information on quality perception. Some researchers claim that sales promotions affect not only purchase decisions but also quality perceptions (Krishna et al. 1991, Hunt and Keaveney 1994, Papatla and Krishnamurthi 1996, Buchanan et al. 1999). Nevertheless, the effect of price markdown on perceived quality has rarely been examined (Blattberg et al. 1995). We believe we are among the first to investigate the impact of available price information in a markdown strategy on quality perception, estimate a functional relationship between quality and discount, and link it to the retailer's markdown pricing strategy. In this thesis, we take both an empirical and an analytical approaches for modeling the consumer's quality perception as it relates to his/her purchase decision. In contrast to prior work, our behavioral studies, instead of focusing on a single factor (sale price), investigate multiple factors (arrival time, price, discount, product category, demographics) in a more systematic way. Lastly, we incorporate this in an analytical framework to determine the retailer's optimal markdown pricing.

1.2 Research Setup and Methodology

We consider a retailer who sells one product over two periods, referred to as Period 1 and Period 2. The product is sold at its original price in Period 1, but may be marked down to a lower price in Period 2. A fraction of consumers arrive in Period 1. We call them "early consumers." The remaining fraction of consumers who arrive in Period 2 are called "late consumers." Early consumers observe the product sold at its original price, and they are aware that the seller may apply markdown to it in Period 2. The actual discount level is not pre-announced, but the availability of the product in Period 2 is guaranteed. These early consumers choose among three purchase options: (i) buying the product right away, (ii) waiting for the potential discount and returning in Period 2, or (iii) leaving the market without buying anything. For those who wait and return in Period 2, they join the late consumers and observe the same product offered at either the original price or at a discounted price. All consumers present in Period 2 either buy the product or leave the market without buying.

We model the aforementioned research setup as a two-level decision problem. The lower level models the consumers' purchase decisions. Consumers need to decide whether and when to purchase the product to maximize their utilities. Both early and late consumers' utilities are affected by their perceived quality and the selling price of the product. We model the consumers' perceived quality based on our experimental data. In addition, early consumers form an expectation of the potential discount in Period 2. If the expected discount differs from the realized discount, early consumers would experience a gain or a loss due to this discrepancy. Therefore, early consumers also take into account such anticipated gain or loss when making decisions in Period 1. The second level models the retailer's price optimization while taking into account consumers' purchase decisions in response to the retailer's pricing decisions.

Our approach consists of two steps: (i) empirically examining how consumers' perceived quality is influenced by available price information and the time of arrival to the market among other factors, and (ii) characterizing the retailer's optimal markdown strategy when incorporating the consumers' quality perception. In step (i), we design and conduct a consumer purchase experiment to study consumer behavior under different markdown scenarios for different product categories. The experiment examines how perceived quality may be affected by the original price, the level of discount, the arrival time of the consumer, demographics, and product categories. The data collected enable us to derive functional structures that best describe the relationship between perceived quality and price and available price information for both early and late consumers. These empirically validated functional relationships are then incorporated into the modeling analysis of the retailer's price optimization problem. In what follows, we first discuss the design and analyses of our consumer purchase experiment, followed by the discussion of the analytical model.

Chapter 2

Design and Analyses of the Consumer Purchase Experiment

We conducted two studies within the Consumer Purchase Experiment to better understand how consumers develop perception of product quality from price information and how such perception influences their purchase decisions. In study 1, we investigate the impact of arrival times and price markdowns on consumers' quality perceptions and purchase decisions in a two-period setting, where markdown may happen in the second period. In study 2, we employ a within-subject design to examine how consumers may change their quality perceptions when a product is offered at various discount levels, and the impact of their gender and the product's characteristics on the relationship between perceived quality and price information.

2.1 Study 1

In study 1, participants were instructed that they were looking to purchase a new dress shirt or a new blouse, depending on their gender. We manipulated their arrival time to the store, the original price, and the discount level of the product. We address three main questions in this study: (i) How does the original price affect early consumers' quality perceptions? (ii) Do early consumers who decide to wait for a markdown update their quality perceptions when observing the markdown in

Period 2? (iii) How do the original price and the discount level affect late consumers' quality perceptions?

2.1.1 Method

Study Design

We use a 2 (arrival time: early vs. late) $\times$ 3 (original price: \$35, \$70, \$105) $\times$ 4 (discount level: 0%, 30%, 50%, 70%) full factorial between-subject design. Participants are randomly assigned to one of these 24 experimental conditions, and each participant only experiences one condition. We assign participants in a balanced way such that each condition involves approximately 20 participants. Participants assigned to the early arrival time condition (early consumers) arrive in Period 1 when the product is sold at its original price and they are informed that the product may be marked down at a later time. Conversely, participants assigned to the late arrival time condition (late consumers) arrive in Period 2 when the product is already marked down (if any). Manipulating the arrival time of a participant enables us to investigate whether early versus late consumers form quality perceptions differently. The gap between these two periods is fixed to be three months and explicitly shown to the participants. When participants enter the study, they are instructed to imagine that they are looking for a new clothing item. In this study, male (female) participants evaluate a dress shirt (blouse). We choose these products because (i) most people are familiar with and have purchased these items; (ii) these items exhibit less seasonality compared to other apparel items (such as a winter jacket); and (iii) markdown is commonly used in the fashion industry (Pashigian 1988). To avoid potential biases on style preferences, we randomly display the image of one of the two shirts or blouses of similar styles while keeping the product description the same. All shirts and blouses used in the study are shown in Figure 2-1. We design the original prices in our study based on sampling the actual prices of similar items in the market[1]. Having multiple

[1]Specifically, we observe that the average price for a sample of dress shirts sold on Macy's.com is \$70.00. We take the lower (higher) price to be 50% (150%) of this average price and use the same set of original prices for the female products.

original prices allows us to analyze how the original price of a product affects quality perception. A "discount level" indicates the percentage discount revealed to the participants in Period 2. We consider 30%, 50%, and 70% off because they are common discount levels applied in a markdown setting (e.g., All Things Target 2015). We also include a 0% discount level to capture the scenario when there is no markdown on the product.

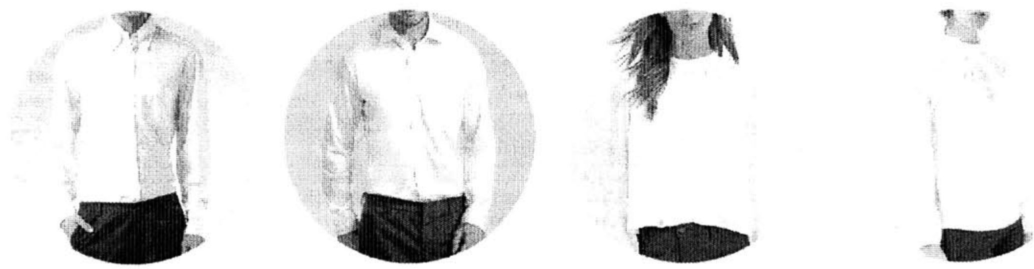


Figure 2-1: Shirts and blouses used in the study

Procedure and Participants

We explain the detailed procedure of Study 1 based on the male version. The female version is implemented in the exact same fashion with the only difference in the product shown (a blouse instead of a dress shirt). The same set of original prices, discount levels, and questions apply to the female version. The study consists of two parts. In Part 1, participants arrive at a virtual clothing store, evaluate the product shown in terms of perceived quality and value, and make their purchase decision. Then, they proceed to Part 2 to answer questions regarding their general experiences of buying similar products and demographics. We recruited 958 participants from Amazon Mechanical Turk for this study (50% male, median age is 33 with a standard deviation of 11.37). The participants received a flat rate of $2 for completing this study, which lasts on average 7 minutes 39 seconds. Recently, the Amazon Mechanical Turk has become more popular among researchers as a valid research environment to conduct experiments for scholarly publications (Paolacci et al. 2010, Buhrmester et al. 2011, Mason and Suri 2012). The flow and experimental conditions of Study 1 are illustrated in Figure 2-2. We next elaborate on the detailed process experienced by a participant in the study.

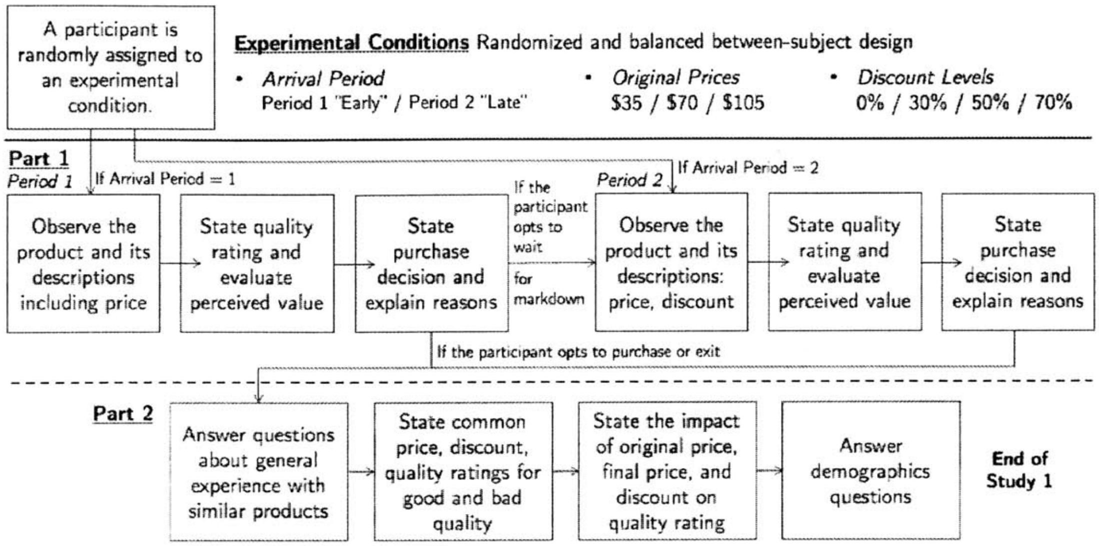


Figure 2-2: Experimental conditions and flow of Study 1

We begin by explaining the sequence of questions faced by an early consumer who is assigned to arrive in Period 1. In *Part 1*, the participant is presented a picture of a dress shirt along with some descriptions on the shirt's characteristics. Among the characteristics, we show the original price of the product and the following statement: "It may be marked down to a lower price in three months. Its price will never go up, and availability is guaranteed even at markdown," (see Figure 2-3). The participant was then asked to state his/her quality rating of the shirt on a continuous 0 - 100 scale. A higher rating means higher quality. We adopt this scale as opposed to the more commonly used 5- and 7-point Likert scales (Wheatley and Chiu 1977, Lichtenstein and Burton 1989, Suk et al. 2012) to elicit a finer quality rating so as to allow for the estimation of a functional relationship between perceived quality and various price information.

Next the participant is asked to state how much he agrees or disagrees with each of the following statements:

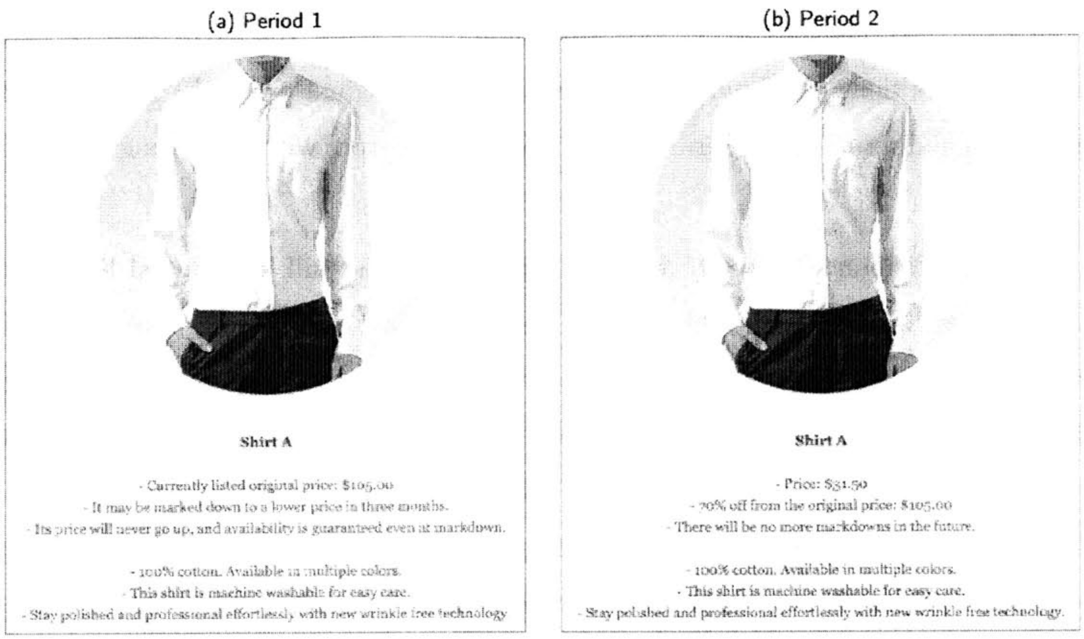


Figure 2-3: Examples of product descriptions from Period 1 and Period 2

(i) "This product contains the features that I want."

(ii) "Judging from the price, this product is likely to have a good quality."

(iii) "Products sold at this price are often NOT reliable."

(iv) "My family and friends will likely agree that I should buy this product."

(v) "I am willing to pay [*price*] for this product."

We design these statements by modifying the composite perceived value framework, an established survey instrument to assess a consumer's perceptions of service value in four dimensions: emotional, social, price/value for money, and performance/quality (McDougall and Levesque 2000, Sweeney and Soutar 2001). These statements allow us to assess each participant's perceived value in different perspectives. While a higher score assigned to the rest of the statements imply higher value, the statement (iii) is intentionally presented in the opposite direction (e.g., a higher score reflects lower quality) in order to check whether the participant is paying attention. The participant is then asked to state the discount level (in % off) he expects to be applied to this shirt in the next three months. Finally, the participant chooses one of three options: (a) buying the shirt now at its original price, (b) waiting for a markdown and returning in Period 2, or (c) leaving the store without buying the shirt.

If the participant chooses to wait for a markdown, he will be directed to Period 2 and shown the exact same shirt again. The participant will be told whether or not the shirt is marked down. If a markdown is indeed applied (randomly determined by the computer), then the participant observes all information shown in Period 1 plus the % off discount applied and the final selling price (see Figure 2-3b for an example). If no markdown is applied, the participant is shown the message "The store did not apply any markdown on this shirt." He is also told that there will be no more markdowns in the future. We then asked the participant if his quality perception for this shirt has changed. If the participant indicates a change in perceived quality, then he will be asked to update his quality rating and perceived value by answering the same set of questions as in Period 1 (through the 0 - 100 scale and perceived value). Finally, the participant chooses one of two options: (a) buying the shirt now or (b) leaving the store without buying. This concludes part 1 of the study.

In part 2 of the study, the participant answers a series of questions regarding their general experience of shopping for shirts (or blouses). Two sets of Likert-scale questions are used to measure the participants' familiarity with similar shirts, as well as how much he thinks prices and discounts impact his quality perception on shirts. The last four questions are designed to elicit four relevant reference points: the typical original price he observes in the market for a new dress shirt, the typical % discount applied to dress shirts, a threshold rating between 0 and 100 such that any product with a quality rating below this threshold would be considered to have a bad quality (referred to as "bad quality threshold"), and another threshold rating between 0 and 100 such that any product with a quality rating above this threshold would be considered to have a good quality (referred to as "good quality threshold"). Study 1 concludes with a set of demographic questions including age, income level, education, and shopping frequency.

For a late consumer assigned to arrive in Period 2, he will observe the shirt with the markdown information (i.e., % discount off and final selling price, or a message showing that no markdown is applied) to begin with. He will then be asked the same set of questions regarding quality ratings, perceived value, purchase decisions, general purchase experience, and demographics. See Appendix B.1 for a sample survey experienced by an early and a late consumer.

2.1.2 Experimental Results

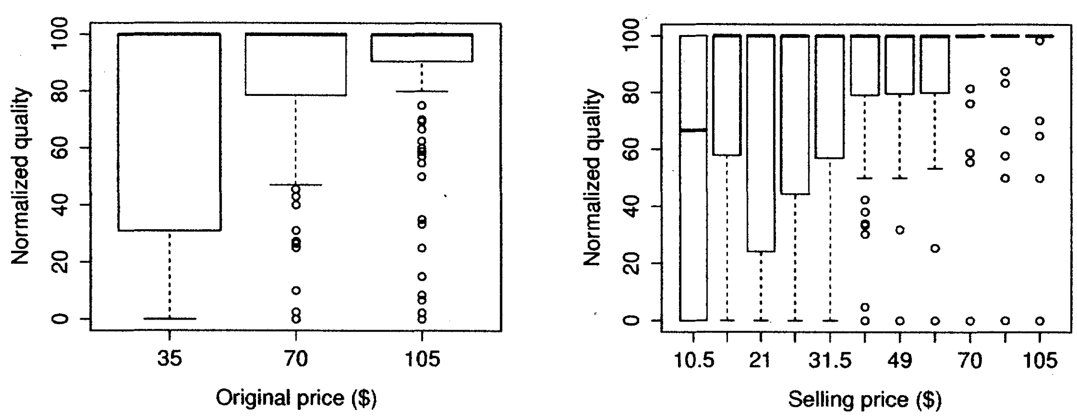
We classify all 958 participants into six groups of consumers based on their arrival periods and purchase decisions. Early consumers are divided into four groups: Early-Buy, Early-Exit, Return-then-Buy, and Return-then-Exit. The first two groups are those who choose to buy the product or exit without buying in Period 1. The last two groups choose to wait for a markdown and either buy the product or exit without buying in Period 2. Late consumers are divided into either Late-Buy or Late-Exit if they choose to buy the product or exit without buying in Period 2. The breakdown of number of participants in each group is shown in Table 2.1.

	Buy	Exit	Return-then-Buy	Return-then-Exit	Total
Early consumers	24	179	190	82	475
Late consumers	189	294	-	-	483
Total	213	473	190	82	958

Table 2.1: Number of participants in each of the six groups

We investigate participants' quality perceptions based on both the raw quality ratings stated by the participants and their normalized quality ratings. We normalize participants' quality ratings given the two quality thresholds they specify in the study: the good (bad) quality threshold corresponds to the threshold rating such that any product with a quality rating above (below) this threshold would be considered to have a good (bad) quality. Consider a participant who states a quality rating of Q, a bad quality threshold of $\underline{Q}$, and a good quality threshold of $\overline{Q}$. Then this participant's normalized quality rating is defined as:

$$Q' = \begin{cases} 0, & \text{if } Q \in [0, \underline{Q}], \\ (Q - \underline{Q})/(\overline{Q} - \underline{Q}), & \text{if } Q \in (\underline{Q}, \overline{Q}), \\ 100, & \text{if } Q \in [\overline{Q}, 100]. \end{cases}$$

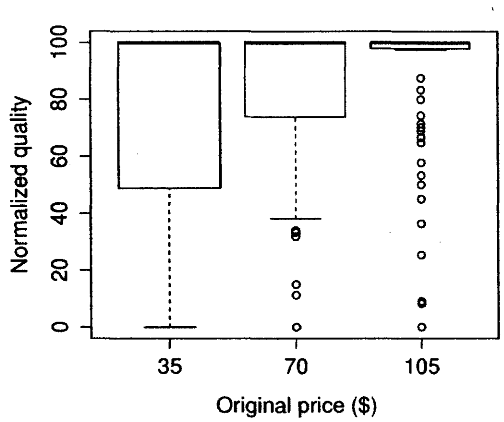


(a) by early consumers in Period 1

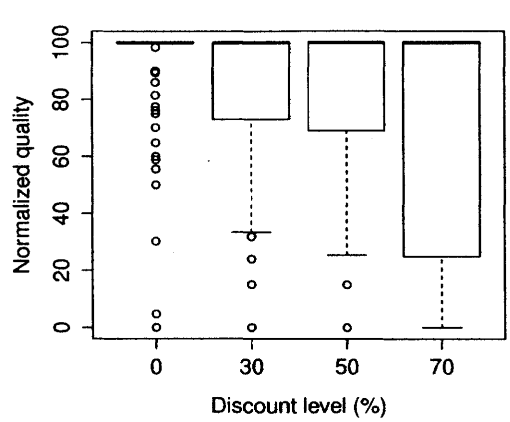
(b) by late consumers in Period 2

Figure 2-4: Normalized quality ratings by the product's selling price

With this normalization scheme, a quality rating above $\overline{Q}$ is considered as good quality and is equalized to $Q' = \overline{Q}$. Similarly, a quality rating below $\underline{Q}$ is equalized to $Q' = \underline{Q}$ to represent bad quality. All quality ratings between the two thresholds are normalized to a scale of 0 to 100. When analyzing participants' quality perceptions based on their normalized quality ratings, we only use data from those participants who report $\underline{Q} < \overline{Q}$ (777 out of 958, 81%). The key benefit of utilizing the normalized quality ratings is to improve comparability of ratings made by different participants in our between-subject design. Figure 2-4 demonstrates how the distribution of normalized quality ratings vary with the selling price in Periods 1 and 2. Figure 2-4a considers quality ratings reported by all early consumers, and Figure 2-4b consid-



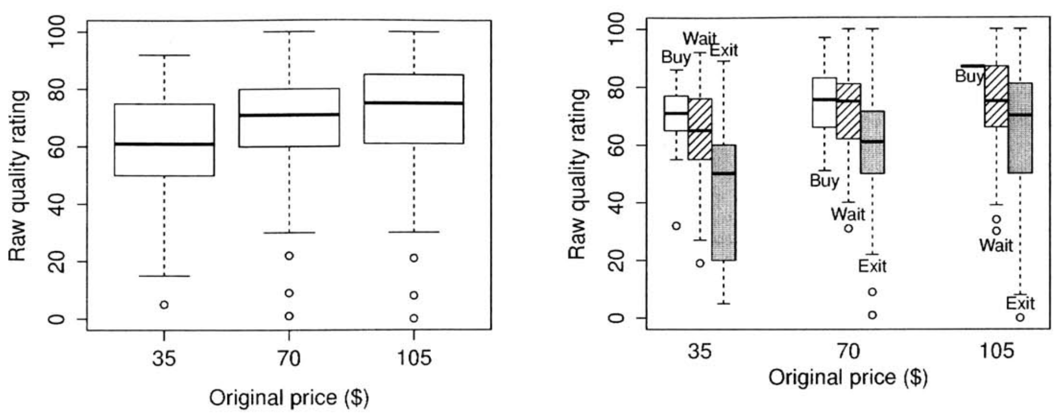
(a) at each original price



(b) at each discount level

Figure 2-5: Normalized quality ratings by late consumers in Period 2

ers quality ratings reported by all late consumers (but does not consider those early consumers who choose to wait for a markdown and indicate a change in perceived quality). In both figures, we observe that (except at the selling price of \$10.5) the median normalized quality is equal to 100; i.e., half of our participants state a quality rating that is at least as high as their good quality threshold. Nevertheless, we observe that as the selling price increases, the gap between the first quartile and the median of the distribution decreases. This observation gives the first evidence that a higher selling price is associated with a higher perceived quality among our participants. Importantly, we confirm that this observation is also true when we analyze participants' quality perceptions based on their raw quality ratings (see Figures 2-6a and 2-8), proving its robustness. These results are aligned with existing findings in the literature that a higher selling price signals higher perceived quality (Rao and Monroe 1988, 1989, Lichtenstein and Burton 1989, Lichtenstein et al. 1991). In addition, Figure 2-5a (2-5b) demonstrate that late consumers' quality ratings increase (decrease) with the product's original price (discount level). In what follows, we focus on answering the three key research questions outlined at the beginning of Study 1. Our subsequent analyses are based on participants' raw quality ratings so that we can utilize all data collected.



(a) at each original price

(b) at each original price, conditional on purchase decisions

Figure 2-6: Raw quality ratings by early consumers in Period 1

(i) How does the original price affect early consumers' quality perceptions?

475 participants are assigned to arrive in Period 1. Figure 2-6b shows the distribution of quality ratings reported by early consumers at each of the original prices conditional on purchase decisions. We observe that given a purchase decision (i.e., buy or wait or exit), there is a positive relationship between perceived quality and the original price. In addition, for all prices, participants who choose to buy or wait generally state higher perceived quality than those who choose to exit without buying. To formally test the relationship between the original price and early consumers' perceived quality, we estimate a simple linear regression with the participants' quality ratings as the dependent variable and the original price as the explanatory variable. Table 2.2b summarizes the regression results.

The coefficient estimate for the original price is positive and statistically significant, confirming our earlier observation from Figure 2-6b. To obtain the best functional characterization of the relationship between the original price and perceived

Dependent variable: Q		
Explanatory variables	P	$P+P^2$
In-sample R^2	6.55%	6.43%
AIC	2006.09	2007.55
Out-of-sample R^2	1.91%	1.72%
MSE	308.55	306.84
MAD	10.94	11.43

(a) Model comparison

	Dependent variable: Perceived quality Q
Original price P	0.164***
	(0.030)
Intercept	54.274***
	(2.287)
Observations	475
R^2	0.059
Adjusted R^2	0.057
Residual Std. Error	18.631 (df = 473)
F Statistic	29.428*** (df = 1; 473)
Note	*p<0.1; **p<0.05; ***p<0.01

(b) Coefficient estimates of the linear model

Table 2.2: The analysis of the functional relationship between perceived quality Q and original price P for early consumers

quality, we perform a stepwise model selection. The most general model considered in the stepwise selection is $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 P_i^3 + \alpha_4 P_i^4 + \alpha_5 \sqrt{P_i} + \epsilon_i$, where subscript i is the participant index, Q_i is participant i's quality rating, P_i is the original price observed by participant i, and ϵ_i is the independent error term. The stepwise model selection process compares different nested versions of this general model that include different subsets of explanatory variables and chooses the model with the best in-sample fit based on the Akaike Information Criterion (AIC, Bozdogan 1987).[2] The process shows that the simple linear model performs the best among all candidate models. Therefore, we conclude that *early consumers' quality perceptions in Period 1 increase with the original price of the product, and a linear model in the original price characterizes this relationship well.*

(ii) Do early consumers who decide to wait for a markdown update their quality perceptions when observing the markdown in Period 2?

We next examine whether early consumers who choose to wait for a markdown change their quality perceptions when they observe the discounted prices in Period 2. Out of the 272 early consumers who choose to wait, only 38 (13.97%) of them report a change in their quality ratings in Period 2.[3] Among these 38 participants, the average percentage change in their quality ratings is 1.77%, with the first quartile, median, and third quartile being −22.75%, 3.71%, and 22.43%. For all returning consumers, we test whether the mean of their quality ratings in Period 1 is the same as the mean of those in Period 2 using the Wilcoxon within-subject paired test. The result suggests that we are unable to reject the null hypothesis that the they are equal ($V = 397.5$, $p = 0.7006$). Therefore, we conclude that *early consumers who choose to wait for a markdown rarely update their quality perceptions after observing the markdown in*

[2]AIC is a common measure of goodness of fit that favors smaller residual error but penalizes for including too many predictors to avoid overfitting.

[3]One may question that participants do not report a change in perceived quality due to convenience; i.e., they do not want to answer additional questions about their updated quality ratings. To mitigate this concern, we do not show these additional questions unless a participant has stated that his/her quality rating has changed. Participants cannot change their response once they have answered whether or not their quality perceptions have changed.

Period 2.

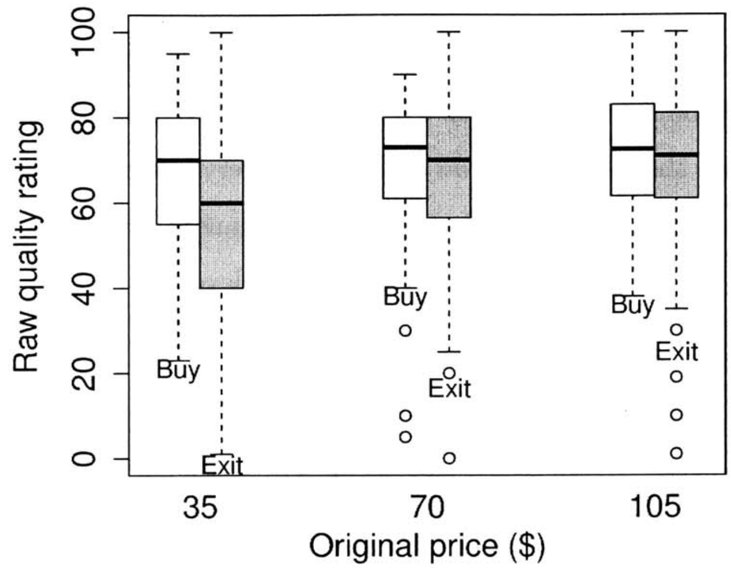


Figure 2-7: Quality ratings by late consumers in Period 2 at each original price, conditional on their purchase decisions

(iii) How do the original price and the discount level affect late consumers' quality perceptions?

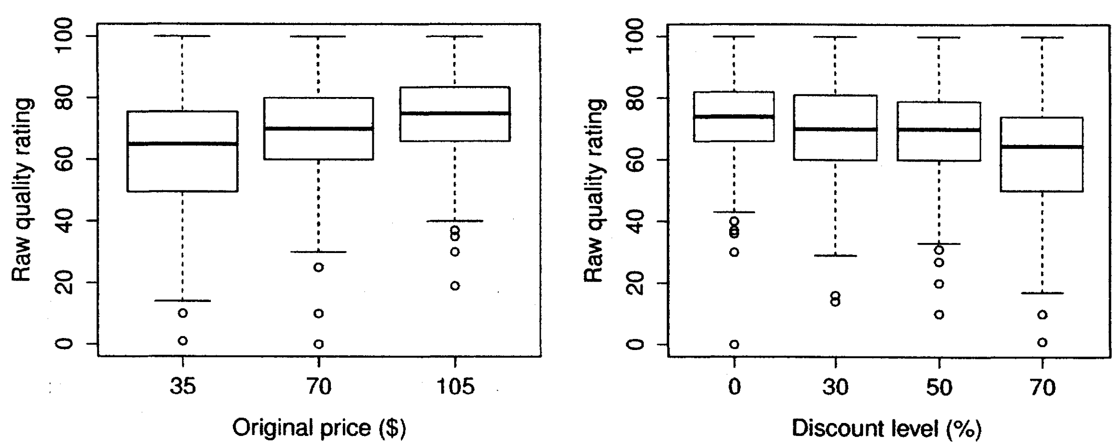
483 participants (50.42%) are assigned to arrive in Period 2. Figure 2-7 shows their quality ratings at each of the original prices conditional on their purchase decisions. Similar to early consumers, late consumers who choose to buy the product state a higher quality rating than those who exit without buying. For late consumers, they observe three pieces of price information: the product's original price, the final selling price, and the percentage discount applied. We investigate how these three pieces of information jointly influence late consumers' quality perceptions.

First, we determine that the final selling price has a minimal impact on late consumers' quality perceptions. To achieve this result, we compare two nested models:

(i) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \epsilon_i$,

(ii) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \alpha_3 S_i + \epsilon_i$,

where Q_i, P_i, D_i and S_i are the quality rating by participant i, the original price, the percentage discount, and the final selling price observed by participant i. The likelihood ratio test shows that the two models have very similar explanatory power ($\chi^2 = 0.0027, p = 0.96$), suggesting that the late consumers' quality perceptions are mainly affected by the original price and the discount level.



(a) at each original price

(b) at each discount level

Figure 2-8: Raw quality ratings by late consumers in Period 2

Focusing on the original price and the discount level, our next step is to derive a functional relationship between these factors and participants' perceived quality that can explain our data well. To start, we estimate a simple linear regression with the participants' quality ratings as the dependent variable and both the original price and the discount level as explanatory variables. The regression results are summarized in Table 2.3. The coefficient estimates for the original price and the discount level are statistically significant. The original price is found to have a positive effect on quality, while the level of discount has a negative impact, agreeing with our observation in Figure 2-8.

	Dependent variable:
	Quality perception Q
Original price P	0.154***
	(0.030)
Discount level D	−0.143***
	(0.032)
Intercept	60.630***
	(2.454)
Observations	483
R^2	0.089
Adjusted R^2	0.085
Residual Std. Error	17.954 (df = 480)
F Statistic	23.323*** (df = 2; 480)
Note	*p<0.1; **p<0.05; ***p<0.01

Table 2.3: Coefficient estimates of model (a)

For our model selection, we consider both in-sample fit and out-of-sample prediction when determining the best functional relationship. We consider four models with different sets of explanatory variables:

(a) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \epsilon_i$,

(b) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \alpha_3 D_i^2 + \alpha_4 D_i^3 + \epsilon_i$,

(c) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 D_i + \alpha_4 D_i^2 + \alpha_5 D_i^3 + \epsilon_i$, and

(d) $Q_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 D_i + \epsilon_i$.

Model (a) is the most parsimonious model capturing both factors. Model (b) is the final model selected by the stepwise model selection process, which starts with a general model that contains polynomials of P_i and D_i up to the fourth degree, $\sqrt{P_i}$, and $\sqrt{D_i}$. Models (c) and (d) are the last two models eliminated by the stepwise selection process. To systematically examine these models' in-sample fit and out-of-sample prediction, we perform a 5-fold cross validation for each model. Specifically, we first randomly partition the data into 5 equal-sized subsets in a stratified manner; i.e., we ensure that the proportion of data points corresponding to each parameter combination in the experiment (regarding gender, original price, and discount level) is the same in each subset as in the entire data. Next, we treat each subset as a hold-out sample, use the other 4 subsets as the training data to estimate the model coefficients, and predict the quality ratings for the hold-out sample. We perform this estimation and prediction for each subset given a random partition, which constitutes one iteration of a 5-fold validation. After one iteration, we compute the averages of the coefficient estimates and a few performance measures for both in-sample fit (adjusted R^2, AIC) and out-of-sample prediction (out-of-sample adjusted R^2, mean squared errors or MSE, and mean absolute deviation or MAD). We repeat this validation for 100 iterations, using a different random partition in each iteration. Based on these 100 iterations, we finally compute the 95% confidence intervals for the above performance measures. The results are summarized in Table 2.4.

We first note that for the various performance measures, the higher the adjusted R^2 values, the better the model performs. Conversely, the lower the other measures (AIC, MSE, MAD), the better the model performs. In Table 2.4, we use the notation $*$ to indicate which of the four models performs best with respect to a certain measure. We observe that model (a) outperforms the other models in all 5 measures, although all 4 models have fairly similar performance. Hence, our analysis shows that model (a) can explain our data well both in- and out of sample.[4] Referring back to Table 2.3, we note that the coefficients for the original price and the % discount level are significantly positive and negative, respectively. These statistical results and our model selection demonstrate that *late consumers' quality perceptions increase with the original price but decrease with the discount level; in addition, a linear model in*

[4] To verify the robustness of this conclusion, we test a set of alternative models in which the % discount is replaced by the discount value in dollars. We reach the same conclusion as before.

both the original price and the discount level characterizes these relationships well. Our findings thus extend the literature on price–quality relationships by measuring the joint impact of the original price and the discount level on consumers' perceived quality in a markdown setting.

Dependent variable: Perceived quality Q

	Model (a)	Model (b)	Model (c)	Model (d)
Predictors	$P_1 + D$	$P_1 + D + D^2 + D^3$	$P_1 + P_1^2 + D$	$P_1 + P_1^2 + D + D^2$
In-sample R^2	[6.48%, 6.56%]*	[4.76%, 4.89%]	[3.57%, 3.73%]	[5.34%, 5.45%]
AIC	[1118.550, 1118.803]*	[1119.824, 1120.095]	[1121.055, 1121.361]	[1119.768, 1120.051]
Out-of-sample R^2	[7.95%, 8.99%]*	[7.77%, 8.84%]	[7.33%, 8.43%]	[7.54%, 8.63%]
MSE	[319.1211, 330.3682]*	[319.6706, 330.5621]	[321.2585, 332.0594]	[320.5336, 331.764]
MAD	[10.98834, 11.31422]*	[11.07246, 11.36372]	[11.07771, 11.32759]	[10.98474, 11.3263]

Table 2.4: Model comparison: Functional relationship between perceived quality Q, original price P, and % discount D

2.2 Study 2

In Study 2, we further examine the functional relationship between perceived quality, the product's original price, and the discount level with a finer within-subject manipulation of the latter two factors. We also investigate this relationship for different product categories and a different population that has distinctive socio-demographic characteristics compared to Amazon Mechanical Turk workers.

2.2.1 Method

Study Design

The key treatment variables in this study are the original price, the discount levels, and the product category. We consider three product categories: regular fashion, luxurious fashion, and hi-tech products. Each category consists of 2–3 different products, with the fashion items being gender-specific and the hi-tech products being gender-neutral (see Figure 2-9 for the complete list of products included). Each product has a fixed original price, while different products may have different original prices.[5] We divide the possible discount levels into four groups: very small (10% or 15% off), small (20%, 25%, or 30% off), large (40% or 50% off), and very large (60% or 70% off). Each participant evaluates three products, one from each category, in a random order. For gender-specific products, we assign them to participants with the corresponding gender; i.e., male (female) participants evaluate male (female) products. For each product, participants observe the original price and four discount levels, one in each discount group mentioned above. The original price is always shown first, and the four discount levels are shown in a random order. Participants are asked to state their quality ratings for each price point they observe. We assign products and discount levels to the participants randomly and uniformly to ensure balanced sample sizes across different parameter combinations.

[5] The original prices of all products in Study 2 are: shirt/top \$69.90, shoes/flats \$115.00, wallet/handbag \$350.00, winter coat \$375.00, watch \$795.00, digital camera \$798.00, and HDTV \$999.99.

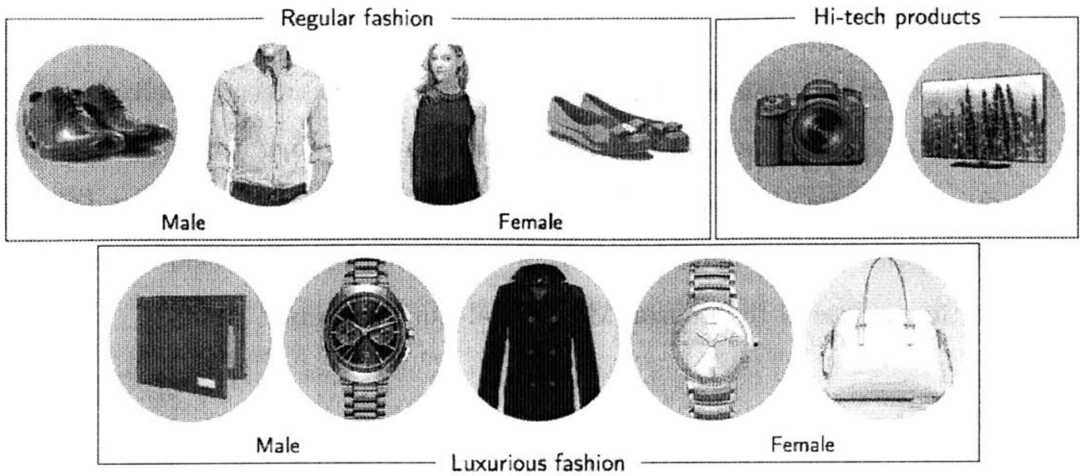


Figure 2-9: Products shown in Study 2

Participants and Procedure

The participants in Study 2 are 57 Executive MBA (EMBA) students from a business school of an elite university in the northeast of the United States (73.68% male, median age is 40 with a standard deviation of 6.41). The students participated in this study as an optional assignment in one of their core courses. We follow a similar procedure as in Study 1. The key differences are (i) we do not distinguish the arrival timing of a participant; (ii) each participant is shown multiple scenarios with different discount levels in a random order, and (iii) each participant evaluates three different products in a random order. The participants state their quality ratings on a scale of 0–100 and their purchase intentions for each of the five price points (the original price and four discount levels) they observe. Figure 2-10 shows the flow of Study 2 (also see Appendix B.2 for a set of sample questions for one of the products). After participants complete their quality ratings, they answer a similar survey as in Study 1 consisting of Likert-scale and open-ended questions about the reasons behind their decisions, their prior experiences with similar products, and demographics.

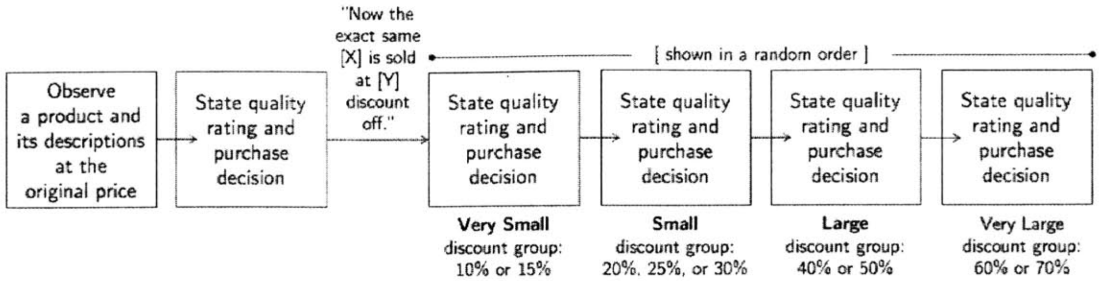


Figure 2-10: Flow of Study 2

2.2.2 Experimental Results

We first analyze whether we obtain in Study 2 the same insight as in Study 1 that perceived quality decreases with deeper discount. Since we utilize a within-subject design that exposes each participant to multiple discount levels, we can characterize the relationship between perceived quality and the discount level for each participant individually. To do so, we first define a participant's normalized quality rating for a product at a discount level to be his/her raw quality rating of the product at the discount divided by his/her raw quality rating of the product at the original price. That is, the normalized quality rating captures the difference of quality perception at a discounted price relative to that at the original price. We focus on normalized quality ratings to improve comparability across different products (which have different original prices) and different participants.

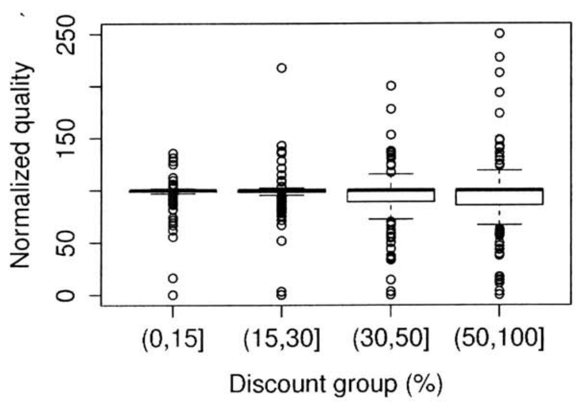


Figure 2-11: Normalized quality for each discount group

Figure 2-11 shows the distribution of normalized quality ratings for each discount group tested in the Study. We observe that the participants' normalized quality ratings form a more dispersed distribution under a deeper discount. That is, as the discount becomes deeper, there exist more deviations in the participants' quality perceptions relative to their quality perceptions at the original price. We next investigate further the individual patterns behind these deviations.

Q-D Patterns	Fixed	QDD	QID	Mixed	Total
# Data Points	300	260	90	105	755
Percentage	39.74%	34.44%	11.92%	13.91%	100%

Table 2.5: Quality-discount patterns observed from the data

For each participant-product pair, we define four different patterns of how quality perception varies across discount levels. Table 2.5 presents the four patterns and the number of data points following each pattern. Under the "fixed" pattern, quality perception is not affected by the discount level at all. In our sample, close to 40% of the data follow the fixed pattern. Under the "QDD" pattern, quality perception decreases with a deeper discount, and about 34% of the data demonstrate this pattern. The other two patterns constitute a small fractions of the data: 12% of the data follow the "QID" pattern where quality perception increases with a deeper discount, and 14% of the data follow the "mixed" pattern where there is not a monotonic relationship between quality perception and discount. Examining the participants' responses to the post-experiment survey, we find that participants exhibiting these last two patterns tend to interpret quality perception differently as associated with purchase satisfaction or the perceived value of the product. Here are some representative quotes from these participants' responses.

- "I can get just as more quality at a lower price. I bought the shoes [...] from JC Penny. I got them for $30 and they are as good quality as the $115.00 shoes."
- "If the initial price was high, the quality tended to be higher from inherent

quality, but if there was a huge discount, that increased this initial quality even more, because it become even more alluring with the deep discount."

- "I thought that the discounted price might actually be its recommended selling price and I was fooled into thinking it was a better quality product."

Characterization of the relationship between perceived quality and the discount level

Following our approach to the analysis of Study 1, we first determine which factors among the product's original price, final selling price, and discount level are statistically significant in signaling the consumers' perceived quality. Let $\overline{Q}_i$, P_i, D_i, and S_i be participant i's normalized quality ratings, the original price, percentage discount level, and final selling price of the product observed by participant i, respectively. We again compare between the following two nested models: (i) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \epsilon_i$ and (ii) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \alpha_3 S_i + \epsilon_i$. The likelihood ratio test fails to reject the null hypothesis that adding the final selling price S_i (ii) does not improve the significance of Model (i) ($\chi^2 = 2.6626, p = 0.1054$).

In 4.1.2 (iii), we have found that the simple linear model of perceived quality based on the product's original price and discount level is the best at approximating the data in Study 1. Prior to refining the model for Study 2's within-subject data, we perform a model selection, similar to our analysis in Study 1, to test the performance of the linear model under this setting. Four models under our consideration are:

(a) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 D_i + \epsilon_i$,

(b) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 P_i^3 + \alpha_4 P_i^4 + \alpha_5 \sqrt{D_i} + \epsilon_i$,

(c) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 P_i^3 + \alpha_4 P_i^4 + \alpha_5 \sqrt{D_i} + \alpha_6 D_i^2 + \epsilon_i$, and

(d) $\overline{Q}_i = \text{Intercept} + \alpha_1 P_i + \alpha_2 P_i^2 + \alpha_3 P_i^3 + \alpha_4 P_i^4 + \alpha_5 D_i + \alpha_6 \sqrt{D_i} + \alpha_7 D_i^2 + \epsilon_i$.

Model (a) is the simple linear model which has performed well fitting the between-subject data. The remaining three models are the last models found through the stepwise model selection process with the same set of initial exploratory variables as in Section 4.1.2 (iii). The order of model elimination is: Model (d), then Model (c), and then Model (b) as the final model. Due to a smaller data set, we examine these four models through a simple stratified 70/30 training-testing validation. We report in Table 2.6 the expected values of each of the performance measures (adjusted R^2, AIC for in-sample fit; adjusted R^2, MSE, and MAD for out-of-sample prediction) across 100 validation runs.

In contrast to the result of Study 1, we observe that Model (a) (linear) does not outperform the other models. However, the performances of the four models are fairly similar. As Model (b) performs the best in two metrics (tied with Model (c), but simpler), we then analyze the mixed-effects model under Models (a) and (b) to test their performances under the within-subject setting. Tables 2.7 and 2.8 present the results of Model (a) and Model (b), respectively. From a comparison between the standard deviations of the random effects, the product variability is not as significant as the variability across different subjects to each participant's quality rating. The linear model (a) performs better than the other in terms of the AICs and BICs. The linear discount is found to be statistically significant in the fixed effects, while the original price is not.

Dependent variable: Normalized quality $\overline{Q}$				
	Model (a)	Model (b)	Model (c)	Model (d)
Predictors	$P+D$	$P+...+P^4+\sqrt{D}$	$P+...+P^4+D^2+\sqrt{D}$	$P+...+P^4+D+D^2+\sqrt{D}$
In-sample R^2	1.70%	2.41%*	2.27%	2.15%
AIC	4409.394	4407.235*	4409.235	4411.066
Out-of-sample R^2	4.60%	5.88%	5.89%*	5.86%
MSE	366.4012	361.4660	361.4279*	361.4978
MAD	4.8214*	5.1078	5.1222	5.0136

Table 2.6: Model comparison: Functional relationship between normalized quality $\overline{Q}$, original price P, and % discount D

Random Effects	Name	Variance	Std. Dev.
Individual	(Intercept)	224.97	14.999
Product	(Intercept)	11.91	3.451
Residual		245.31	15.662

Number of obs: 985, groups: Individual, 57; Product, 10

	Fixed Effects
	Normalized quality $\overline{Q}$
Original price P	0.005 (0.004)
Discount level D	-0.103^{***} (0.023)
Intercept	97.087^{***} (2.941)
Observations	985
Log Likelihood	−4,198.254
Akaike Inf. Crit.	8,408.509
Bayesian Inf. Crit.	8,437.865
Note	*p<0.1; **p<0.05; ***p<0.01

Table 2.7: Model (a): Mixed-effects model results

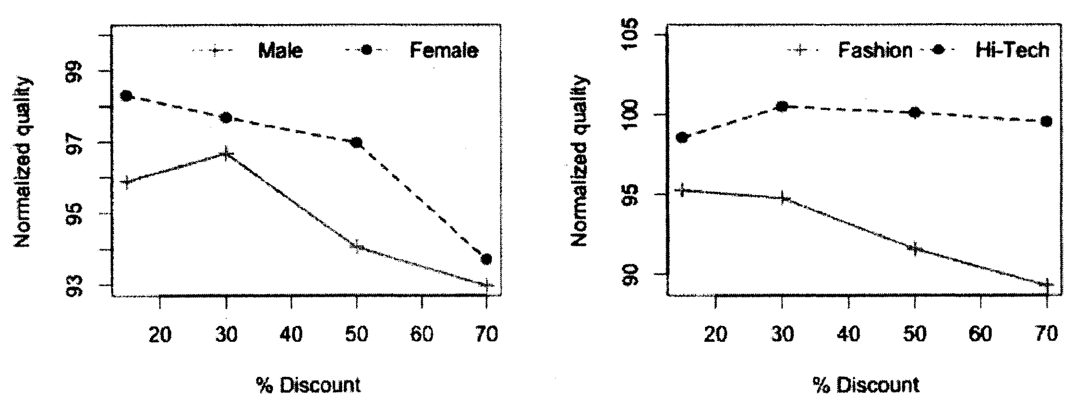
Random Effects	Name	Variance	Std. Dev.
Individual	(Intercept)	225.64	15.021
Product	(Intercept)	6.286	2.299
Residual		245.682	15.674
Number of obs: 985, groups: Individual, 57; Product, 10			

	Fixed Effects
	Normalized quality $\overline{Q}$
Original price P	0.055 (0.147)
(Original price)^2	−0.0001 (0.001)
(Original price)^3	0.00000 (0.00000)
(Original price)^4	0.000 (0.000)
$\sqrt{\text{Discount level (\%)}}$	−0.852*** (0.195)
Intercept	94.544*** (9.271)
Observations	985
Log Likelihood	−4,240.529
Akaike Inf. Crit.	8,499.058
Bayesian Inf. Crit.	8,543.092
Note	*p<0.1; **p<0.05; ***p<0.01

Table 2.8: Model (b): Mixed-effects model results

Demographics and product characteristics

We further investigate the effects of a participant's gender and a product category he/she observes on his/her perceived quality. By looking at the plots of the average normalized quality versus the discount level for each gender and for each product category in Figure 2-12, we observe potential effects of these characteristics on the quality-price relationship. We then analyze the maximum likelihood fit of the following linear mixed models. Model A or a null model, which only includes an intercept, and Model B1, which takes the original price and the discount level as additional explanatory variables, are used as our benchmarks. The gender/product characteristic's effects are introduced in Models B2 and C. Model B2 extends Model B1 by adding two binary variables *Male* (being 0 for female and 1 for male subjects) and *Tech* (being 0 for fashion and 1 for tech products). Lastly, Model C further extends Model B2 by adding the interaction terms between gender/product category and the original price and/or the discount level. For each of these models, we perform likelihood ratio test against Models A and B1 to verify whether additional explanatory variables are statistically significant. The results from the linear mixed models and likelihood ratio tests are displayed in Table 2.9. Without the information about a participant's gender or product category, the product's original price and discount level are significant predictors for perceived quality as we observed before. When the gender/product category information is available, Model C achieves the lowest AIC and BIC, and some of the interaction terms are found to be significant. Male participants consider the relationship between quality and original price to be weaker than female participants do. Under the same original price and discount level, hi-tech products are generally perceived to have lower quality than fashion items. While the relationship between perceived quality and the original price is stronger for hi-tech products, their quality-discount relationship is weaker than for fashion products.



(a) by the participant's gender (b) by the product category

Figure 2-12: Average normalized quality at each discount group

Dependent variable: Normalized quality $\overline{Q}$

Model	AIC	BIC	*Fixed effects*	*Likelihood ratio test*	
			Significant explanatory variable(s)	χ^2 (p-value) against A	χ^2 (p-value) against B1
A: Null	6483.3	6497.1	$+1$	-	-
B1: Main: $P + D$	6439.2	6462.3	$+1 + P - D$	48.06 (3.663e-11)	-
B2: Main: $P + D$ $+Male + Tech$	6442.7	6475.1	$+1 + P - D$	48.556 (7.227e-10)	0.4954 (0.7806)
C: Interactions	6403.8	6454.7	$+1 - P \cdot Male - Tech$ $+P \cdot Tech - D + D \cdot Tech$	95.423 (2.2e-16)	47.362 (1.584e-08)

Note 1 represents the Intercept term in a regression model.
The sign (plus or minus) in front of each explanatory variable represents the direction of its effect (positive or negative) on the normalized quality.
$X \cdot Y$ represents an interaction term between two explanatory variables: X and Y.

Table 2.9: Linear mixed model fit by maximum likelihood

2.3 Managerial Insights

Our consumer purchase experiment provides us with several interesting insights into how consumers develop quality perceptions given available price information. The following four key findings are the foundation of our modeling analysis discussed in Chapter 3.

Consumers' initial quality perception

For a consumer who has previously seen a product, his/her perception of the product's quality remains the same regardless of a subsequent markdown. In other words, new information about the discount has no impact on quality perception if the perception was already formed. In our setting, which the availability of the product during a markdown period is guaranteed, some early customers will opt to wait for a potential markdown because they believe they would be able to pay a cheaper price for the same product with the same quality. From a retailer's perspective, applying a markdown strategy will encourage some early consumers to delay their purchases to Period 2 instead of paying the original price. This could hurt the retailer's revenue if the majority of consumers arrive early.

The relationship between quality perception and the product's price information

Early consumers use the product's original price as a signal for the product's quality; a higher price implies higher quality. Late consumers use both the original price and the current discount level to make a quality judgment. Interestingly, the final selling price is not a significant signal for quality. We found that, the higher the original price is, the higher quality consumers perceive. On the other hand, the deeper discount suggests a lower quality. Such impact is, however, not as strong as the original price's.

Quality perception decreases linearly with discount

For a product offered at various discount levels, consumers use the product's original price (and their initial quality perception) as a reference and update their perception with regard to the discount level they observe. Within the same consumer, his/her quality perception decreases linearly with a steeper discount. The retailer should be aware of this linear and negative relationship when deciding on the discount level in order to match the market segmentation well.

The impact of demographics and product categories on the relationships

The relationship between quality perception and price information can be further enriched by taking into account the effects of consumers' gender and product category. Female consumers are likely to rate a higher quality for the same product than male consumers. For retailers whose products are marketed to one particular gender, they must realize how consumers of that gender develop a quality perception differently than the others. In contrast, the impact of product category, though significant, does not have a clear direction. While hi-tech products are likely to be rated as lower quality than clothing items with the same original price and same discount level, the actual perceived quality depends on the interplay between product category and quality-price relationship.

Chapter 3

The Model

We consider a monopolistic retailer who sells a single product over two periods: Period 1 and Period 2. The retailer offers the product at its original price (p) in Period 1, and may apply a markdown in Period 2. The retailer's goal is to optimize the amount of the discount (Δ), which is the original price (p) minus the final selling price ($p-\Delta$), in Period 2 in order to maximize revenue. Consumers are classified into two groups based on their arrival time to the market. Early consumers arrive in Period 1 while late consumers arrive in Period 2. We denote $\gamma \in (0,1)$ as the fraction of the population who arrives early. After observing the product, the early consumers can choose to (i) buy the product at the original price now, (ii) wait for a potential markdown, or (iii) leave the market without buying. Those who choose to wait will return in Period 2 when the actual markdown is announced. Late consumers also arrive in Period 2 and observe the product with the discount. Both returning and late consumers choose between buying the product now or exiting the market. The sequence of actions and decisions made by the retailer and the consumers is illustrated in Figure 3-1.

The key trade-off for early consumers is whether to buy the product at the original price or to wait for the potential markdown and hopefully, buy the product at a lower price. In contrast, late consumers buy the product as long as their utility from buying one is higher than not buying it. In what follows, we first focus on building the consumer model in which consumers form their quality perceptions from the available

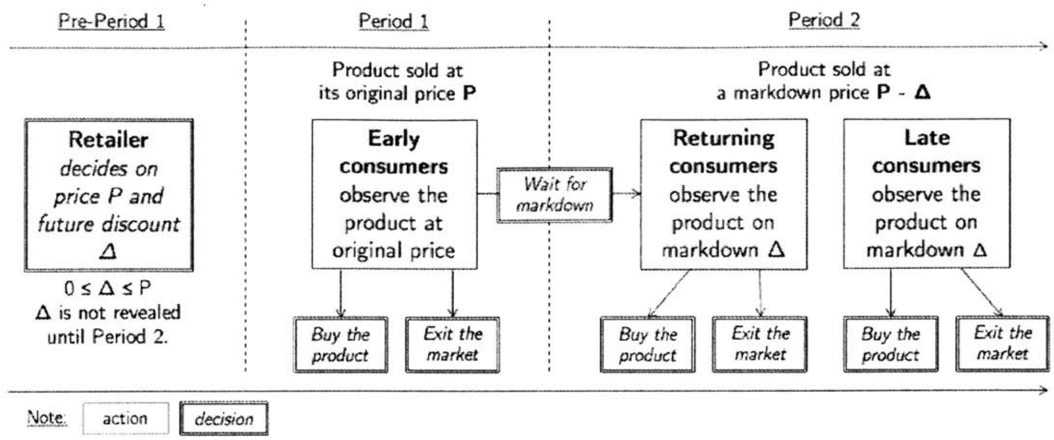


Figure 3-1: The sequence of actions and decisions by the retailer, the early (and returning) consumers, and the late consumers

price information, and then on analyzing the consumers' purchase decisions and the market segmentation. The last phase is to determine the retailer's optimal markdown level and characterize when it is optimal for the firm to apply a markdown strategy to its product.

3.1 The Consumers' Purchase Decisions

In this section, we analyze the consumers' strategic behaviors in the scenario where the retailer sets the product's original price as p and the amount of discount as Δ. Our earlier analysis of the consumer purchase experiment shows that a percentage discount and an absolute amount of discount are interchangeable as an explanatory variable to signal the product's quality. We opt to use the actual amount of discount instead of the percentage one in our analysis because the resulting model is simpler (i.e., $p-\Delta$ is more tractable than $(100-D)P/100$, when D is the percentage discount) while the same insights into consumers' quality perceptions still hold.

3.1.1 Impatience, Optimism, and Reference Dependence

The consumers compare multiple options and choose one that maximizes their utility. If they decide to purchase the product, they can obtain only one unit. Early consumers may weight (or discount) the utility of making a purchase in Period 2 by a factor of $\delta \in (0, 1)$. In this thesis, we define this discounting effect as the "patience" level; a higher δ indicates a consumer who is more "patient" to wait and purchase the product later. Another key parameter $r \geq 0$ reflects the level of "optimism" of the consumers with regard to their expectation about the future discount $r\Delta$. We assume that the consumers are aware that the retailer may apply a markdown to its product in Period 2, but the actual level of discount is unknown to consumers prior to the markdown period. As a result, they may overestimate or underestimate the future discount, which we capture by $r \geq 1$ or $r \leq 1$, respectively. For early consumers who return in Period 2, they may also experience a loss or a gain feeling when the actual markdown level is different than what they expected. We incorporate such effect of loss aversion into the consumers' utility model as an additional gain-loss utility.

To model the early consumers' strategic behavior, we adopt two key behavioral regularities: reference-dependent preferences and loss aversion. Reference-dependent preferences capture a rational equilibrium in beliefs and expectations (Kőszegi and Rabin 2006). Under this setting, a consumer evaluates an overall utility function which consists of two components: a consumption utility and a gain-loss utility. The consumption utility is affected by the satisfaction experienced by the consumer directly, such as the product's price and quality. On the other hand, the gain-loss utility reflects the consumer's feeling of a gain or loss due to a discrepancy in the real outcome from his/her belief or reference point. In a context of shopping, consumers judge the value of a product based on the difference between what is being charged and the reference price formed from their past experience and observation. (Ailawadi and Farris 2013). For instance, if they expect the product to be sold at \$100, seeing it offered at \$80 induces a feeling of gain as they could attain the same product at a cheaper price. On the other hand, they feel a loss when the same product is sold at \$120. Furthermore, consumers are more upset about paying extra \$20 than they would be happy about saving \$20.

In our model, reference dependence appears in the early consumers' behavior as they form an expectation about the future discount and use it as the reference point. Those who choose to return in Period 2 may experience a mental cost of purchasing the product at a different level of discount than what they expected. Therefore, their utility of buying the discounted product in Period 2 is affected by both the consumption utility and the gain-loss utility. Following Kőszegi and Rabin (2006)'s model, we define Ψ as a piecewise-linear gain-loss function, with a steeper slope in the loss region:

$$\Psi(x) = \begin{cases} \eta x, & x \geq 0, \\ 2\eta x, & x \leq 0, \end{cases}$$

where η measures the marginal value of the reference-dependent preferences in comparison to the consumption value. We emphasize the value of a loss more than that of a gain by using 2η in the marginal value of the loss in comparison with η in the gain region.

3.1.2 The Linear Utility Model

Among a number of ways to calculate consumer net utility or surplus, several researchers have used the linear net utility function to capture heterogeneity in the market (Choudhary et al. 2005, Chambers et al. 2006, Kalra and Li 2008). In our approach, we consider the linear utility model such that, for a consumer i, the utility of purchasing an option j is given as:

$$U_j(\theta_i) = \theta_i q_j - p_j \tag{3.1}$$

where q_j and p_j are the the perceived quality and the price of the option j. $\theta_i \sim Uniform[0, \theta_{max}]$ is a *valuation of quality* parameter that captures the consumer i's willingness to pay for the product at a given quality, i.e., a consumer with a higher θ is willing to pay more for the product of the same quality than one with a lower θ. θ_{max} represents the highest valuation of quality in the population. We assume that

θ is privately known to the individual consumer but the retailer only knows that θ is uniformly distributed on $[0, \theta_{max}]$.

From the insights discussed in Section 2.3, we concluded that the early consumers' perceived quality of a product sold at its original price, depends only on the price and will remain unchanged when they observe the product on markdown later. In contrast, the late consumers' quality perception is affected by both the original price and the amount of discount. Quality perception is found increase linearly with price, bit decrease linearly with discount.

In our model, the product is offered at the original price p in Period 1, and is later discounted to $p - \Delta$ in Period 2. Hence, we characterize the perceived quality for an early consumer as q_1 and for a late consumer as q_2 as follows:

$$q_1 = a_1 p \tag{3.2}$$

$$q_2 = a_2 p - c\Delta \tag{3.3}$$

a_1 and a_2 are parameters that measure the marginal effect of the price on the perceived quality. Similarly, c measures the marginal effect of the discount amount on the perceived quality. We model $c < a_2$ as we observed that the impact of the original price is more salient than the impact of the discount amount on quality perception.

An early consumer, with a quality valuation θ and patience level δ, expects the final selling price of the product in Period 2 to be $p - r\Delta$. The utilities of buying the product in Period 1 (U_1) and the utility of waiting to buy in Period 2 (U_w) are as follows:

$$U_1(\theta) = \theta q_1 - p = (\theta a_1 - 1)p$$

$$U_w(\theta) = \delta(\theta q_2 - (p - r\Delta)) = \delta((\theta a_1 - 1)p + r\Delta)$$

If he/she chooses to wait, she will observe the product sold at $p - \Delta$ in Period 2.

We characterize the utility of buying the discounted product in Period 2 as:

$$\begin{aligned}U_2(\theta) &= \theta q_1 - (p-\Delta) + \text{gain-loss utility} \\ &= \theta a_1 p - (p-\Delta) + \Psi(\theta q_1 - (p-\Delta) - \delta(\theta q_1 - (p - r\Delta))) \\ &= \theta a_1 p - (p-\Delta) + \Psi(\theta a_1 p - (p-\Delta) - \delta(\theta a_1 p - (p - r\Delta))),\end{aligned}$$

where $\Psi(x)$ is the gain-loss utility function where x is the difference between the utility of buying the discounted product and the discounted utility of waiting, i.e., $U_2(\theta) - U_w(\theta)$.

3.1.3 Market Segmentation

Next, we analyze the consumers' purchase decisions given the utility formulation for each type of consumer. Early consumers make a decision in Period 1 by comparing among (i) the utility of buying the product at the original price, (ii) the utility of waiting and buying it at the expected discounted price, or (iii) the utility of leaving the market without buying it. Specifically, they will wait and return in Period 2 if and only if $U_w(\theta) > \max(U_1(\theta), 0)$. If they return, they will purchase the discounted product if and only if $U_2(\theta) > 0$. The following proposition characterizes the consumers' purchase decision, from Period 1 given the original price, the discount amount and the behavioral factors. All the proofs are deferred to Appendix A.1.

Proposition 3.1 (Market Segmentation of Early Consumers)
Define the thresholds $\underline{\theta} < \theta_2 < \bar{\theta}$ as follows:

$$\bar{\theta} \equiv \frac{1}{a_1} + \frac{r\Delta\delta}{a_1 p(1-\delta)}, \quad \theta_2(\eta) \equiv \frac{1}{a_1} - \frac{\Delta(1+\eta(1-\delta r))}{a_1 p(1+\eta(1-\delta))} \quad \underline{\theta} \equiv \frac{1}{a_1} - \frac{r\Delta}{a_1 p}$$

such that:

1. *A consumer buys a product at its original price in Period 1 if his/her valuation of quality θ lies in $[\bar{\theta}, \theta_{max}]$, waits for a potential markdown if θ lies in $[\underline{\theta}, \bar{\theta}]$, and leaves the market without buying the product if θ lies in $[0, \underline{\theta}]$.*

2. A returning consumer buys the product with markdown if θ lies in $[\theta_2(\eta), \bar{\theta}]$ and leaves without buying the product if θ lies in $[\underline{\theta}, \theta_2(\eta)]$. In particular, if $r < 1$, then $\theta_2(\eta) < \underline{\theta}$ implying that every returning consumer will buy the product at the discounted price in Period 2.

In Proposition 3.1, we characterize how the market in Period 1 can be segmented given the retailer's markdown strategy. Figure 3-2 visualizes the market segmentation of the early consumers based on their valuation of quality θ and optimism level r. Early consumers who highly value quality (with $\theta \in [\bar{\theta}, \theta_{max}]$) buy the product at the original price in Period 1. Those who value quality less with $\theta \in [\theta_2(\eta), \bar{\theta}]$ wait and buy at the discounted price when they return in Period 2. If the returning consumers are pessimistic (i.e. $r < 1$), they will always buy the product when they return in Period 2 because the true discount level is larger than their anticipated discount, inducing the feeling of gain.

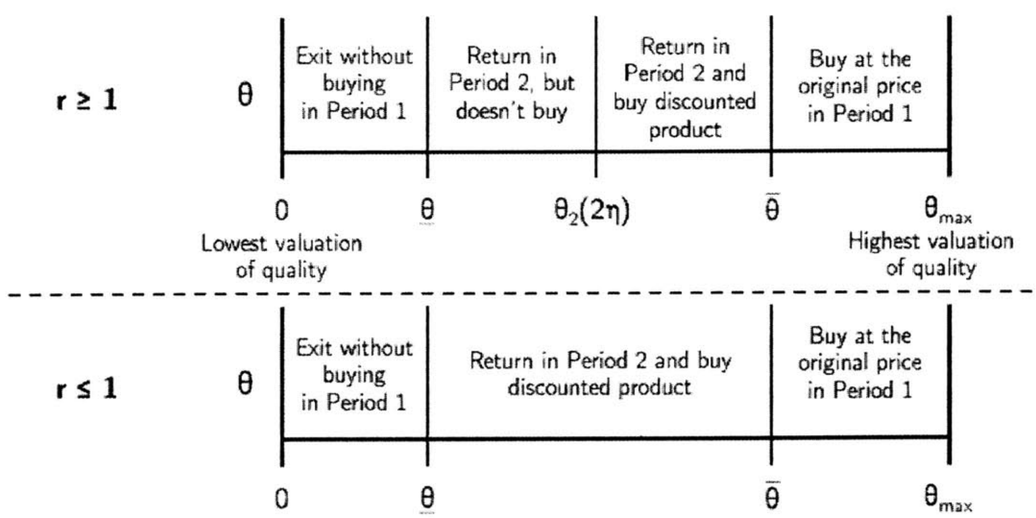


Figure 3-2: Market segmentation of the early consumers who are optimistic ($r \geq 1$) or pessimistic ($r \leq 1$)

For late consumers, they have to decide between only two options: buying the product in Period 2 or leaving without buying. We compare the utility of each option and characterize the late consumers' purchase decisions in the following proposition:

Proposition 3.2 (Market Segmentation of Late Consumers)

Define the threshold $\tilde{\theta}$ *as follows:*

$$\tilde{\theta} \equiv \frac{p - \Delta}{a_2 p - c\Delta}$$

A late consumer buys a product at a discounted price in Period 2 if his/her valuation of quality θ *lies in* $[\tilde{\theta}, \theta_{max}]$, *and does not buy at all if* θ *lies in* $[0, \tilde{\theta}]$.

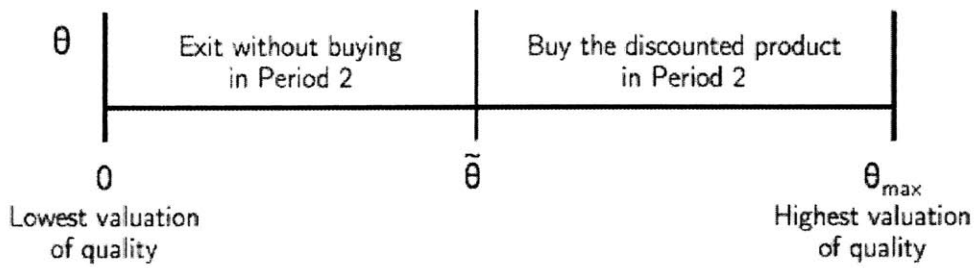


Figure 3-3: Market segmentation of the late consumers

Proposition 3.2 states that, as long as a late consumer's valuation of quality is high enough (i.e., $\theta \in [\tilde{\theta}), \theta_{max}]$, his or her utility of buying the discounted product will be nonnegative, making this option more attractive than exiting the market without buying. Figure 3-3 shows how the late consumers are segmented into two groups based on their valuation of quality and purchase decision. Given the market segmentation of early consumers, we can characterize the resulting fraction of demand from early consumers who purchase the full-price product as D_1 and the markdown product as D_2 Similarly, for late consumers, the resulting fraction of demand from late consumers who buy the discounted product is denoted as D_3. Extending the analyses of the consumers' purchase decisions, the following lemma characterizes the demand from those who purchase the product within (a) the early consumers and (b) the late consumers.

Lemma 3.1

(i) For a market with consumers whose valuation of quality, θ, is a uniform random variable $[0, \theta_{max}]$, the market segmentation is as follows:

	D_1	D_2
$r \geq 1$	$\theta_{max} - \bar{\theta}$	$\bar{\theta} - \theta_2(2\eta)$
$r < 1$	$\theta_{max} - \bar{\theta}$	$\bar{\theta} - \underline{\theta}$

(a) Early consumers who buy the product

	D_3
$r \geq 1$	$\theta_{max} - \tilde{\theta}$
$r < 1$	$\theta_{max} - \tilde{\theta}$

(b) Late consumers who buy the product

Table 3.1: Characterization of demand from consumers who buy the product

(ii) The fraction of early consumers who buy the product in Period 1, D_1, is decreasing in the discount Δ, patience level δ, and optimism level r. The fraction of early consumers who return and buy the product in Period 2, D_2. is increasing in the discount Δ, patience level δ, and optimism level r. Lastly, the fraction of late consumers who buy the product, D_3, is increasing in the discount Δ.

Lemma 3.1 shows how each type of "buying" demand changes with the discount amount Δ. These monotonicity results indicate that applying a deeper discount reduces the demand for the product at full price and stimulates the demand for the discounted product. We observe the same monotonicity results when performing a sensitivity analysis on the patience level δ and the optimism level r.

The demand characterized in Lemma 3.1 allows a retailer to calculate its expected revenue from selling a product under a markdown strategy, taking into consideration the consumers' strategic behavior. In the next section, we take a backward induction approach to examine the retailer's optimal markdown policy. We first analyze the optimal markdown level given the consumers' purchase decisions and demand characterization we previously discussed. Then, we determine the conditions under which applying a markdown strategy yields maximum revenue for the retailer.

3.2 The Retailer's Optimal Markdown Strategy

We consider the setting in which the total market size is known and normalized to 1, and the fraction of the consumers that arrives in Period 1 (early consumers) is given by $\gamma \in [0, 1]$. The retailer sells a product across two periods and its revenue consists of sales in both periods: (i) from early consumers who purchase the product at the original price p in Period 1, and (ii) from returning and late consumers who pay the discounted price $p - \Delta$ in Period 2. Given the original price p and the discount Δ, the retailer's revenue is given by:

$$\begin{aligned}\Pi(p, \Delta) &= \gamma \cdot (\text{Sales from early consumers}) + (1-\gamma) \cdot (\text{Sales from late consumers})\\ &= \gamma\,(pD_1 + (p-\Delta)D_2) + (1-\gamma)(p-\Delta)D_3\\ &= \gamma p(\theta_{max} - \bar{\theta}) + \gamma(p-\Delta)(\bar{\theta} - \max(\theta_2(2\eta), \underline{\theta}))\\ &\quad + (1-\gamma)(p-\Delta)(\theta_{max} - \tilde{\theta}),\end{aligned}$$

where D_1, D_2, and D_3 are the fractions of buying consumers discussed in Lemma 3.1. In this thesis, we investigate the scenario where the product's original price p is fixed and the retailer's objective is to maximize its revenue by choosing the discount amount Δ to apply in Period 2. The retailer's decision problem is formulated in Equation (3.4), and we present its optimal markdown strategy in Theorem 3.1.

$$\left.\begin{aligned}\max_{\Delta} \Pi(p, \Delta) \quad &= \gamma p(\theta_{max} - \bar{\theta}) + \gamma(p-\Delta)(\bar{\theta} - \max(\theta_2(2\eta), \underline{\theta}))\\ &\quad +(1-\gamma)(p-\Delta)(\theta_{max} - \tilde{\theta})\\ \text{s.t} \quad & 0 \leq \Delta \leq p\end{aligned}\right\} \tag{3.4}$$

Theorem 3.1 (Optimal Markdown Strategy)

Under the previous assumptions on the consumer utility and the relationship among quality perception, price, and discount level, the retailer's revenue is a *strictly concave function of price p and discount Δ. The optimal solution (Δ^*) is the unique solution of the following optimality conditions:*

$$\begin{cases} (1-\gamma)\theta_{max} = \dfrac{-\gamma r\delta}{a_1(1-\delta)} + \gamma \dfrac{(r\delta + (1-\delta)(1+2\eta))(p-2\Delta^*)}{(1-\delta)(1+2\eta(1-\delta))a_1 p} & r \geq 1 \\ \quad +(1-\gamma)\left(2\dfrac{(p-\Delta^*)}{a_2 p - c\Delta^*} - c(\dfrac{p-\Delta^*}{a_2 p - c\Delta^*})^2\right), & \\ (1-\gamma)\theta_{max} = \dfrac{-\gamma r\delta}{a_1(1-\delta)} + \gamma \dfrac{r(p-2\Delta^*)}{a_1 p(1-\delta)} & r < 1 \\ \quad +(1-\gamma)\left(2\dfrac{(p-\Delta^*)}{a_2 p - c\Delta^*} - c(\dfrac{p-\Delta^*}{a_2 p - c\Delta^*})^2\right), & \end{cases}$$

Denote $T := \dfrac{1-\gamma}{\gamma} a_1(-\dfrac{2}{a_2} + \dfrac{c}{a_2^2} + \theta_{max})$ and the two thresholds of consumers' optimism $r_1 \leq r_2$ such that:

$$r_1 = \min(1, T), \quad r_2 = \max\left(T, T + \frac{1+2\eta(1-T)}{2\eta\delta}\right)$$

It is optimal for the retailer to apply a markdown strategy on the product, i.e. $\Delta^* > 0$ if and only if $r \in (r_1, r_2)$.

Theorem 3.1 characterizes the optimal markdown solution given the consumers' strategic behavior and the model's parameters. The theorem states that the optimal solution is an interior solution if and only if the optimism level r of the consumers lies in a certain range (r_1, r_2). This shows that it is only profitable for the retailer to apply a markdown strategy if consumers are not too pessimistic or too optimistic about the expected discount, i.e. if their optimism level lies in a certain interval. Intuitively, very pessimistic consumers ($r \leq r_1$) would rather buy the product at the original price while very optimistic returning consumers ($r \geq r_1$) will never purchase the product because of the loss they experience due to the discrepancy between their expected discount and the actual one.

3.3 Managerial Insights

The effects of optimism and patience

Our results show how both strategic motives (patience) and behavioral motives (loss aversion, optimism, quality perception) affect a consumer's purchase decision. In Theorem 3.1, we observe that a retailer's optimal strategy is affected by the optimism and the patience of the consumers. It is optimal for the firm to apply a markdown strategy on the product if consumers are not too optimistic nor too pessimistic about the future discount. Another conclusion from Theorem 3.1 is that this range of optimism is independent of the price. This means that the firm's optimal decision of whether to markdown the product or not is independent of the product characteristics, but rather depends on the consumers' characteristics, particularly their patience, gain-loss behavior, and quality perception.

The effects of patience, when consumers are very patient

In addition, we observe that, when consumers are more patient, the range of consumers' optimism for which the markdown strategy is optimal decreases, leading to more cases where the retailer should not mark down. The intuition behind this result is that, the more patient the consumers are, the more likely they will wait for the discount. Thus, we will have a larger number of returning consumers who do not buy the discounted product as the level of optimism is higher, leading to a smaller optimism range that promotes the optimal markdown strategy. The ultimate case where consumers are extremely patient, i.e. δ=1, is portrayed by the following corollary:

Corollary 3.1

When consumers are extremely patient, i.e. $\delta = 1$. *Denote* $T := \frac{1-\gamma}{\gamma} a_1 \left(-\frac{2}{a_2} + \frac{c}{a_2^2} + \theta_{max} \right)$

(i) If $T < 1$*, then it is optimal for the firm to markdown, i.e.* $\Delta^* > 0$ *if and only if* $r \in \left(T, \max\left(1, 1 + \frac{1 - T - a_1\theta_{max}}{2\eta}\right)\right)$

(ii) If $T \geq 1$*, then it is never optimal for the firm to markdown.*

Corollary 3.1 characterizes the optimal markdown solution when consumers are extremely patient, namely $\delta = 1$, and view the future utility of buying a discounted product to be of the same importance as the current period's utilities. It has the same structure as Theorem 3.1, stating that a markdown strategy is optimal for the firm, if and only if the consumers' optimism lies in a certain interval.

Chapter 4

Numerical Experiments

We consider a product with an original price of $p \in \{\$10, \$50, \$100\}$ to cover different price ranges of products and simulate 10,000 random consumers with the following parameters:

$$a_1, a_2 \in \{2, 3.5, 5, \}, \quad \theta_{max} \in \{1, 10, 100\}, \quad \eta \in \{0.5, 0.8, 2, 6\}$$

and

$$c \in [0, a_2], \quad \gamma \in [0, 1], \quad \delta \in [0, 1], \quad r \in [0, 2]$$

with a step size of 0.005. These ranges are chosen to ensure that some consumers will consider buying the product. The level of optimism r and the level of patience δ are fixed across the population. We assume that the retailer can only apply an integral percentage discount on its product.

4.1 The Impact of Discount on Demand and Revenue

Following Propositions 3.1 and 3.2, and Lemma 3.1, we investigate how the market segmentation changes when the retailer adjusts the discount level. The level of patience and the sensitivity to discount on perceived quality are fixed at $\delta = 0.75$ and

$c = 0.4$, respectively. A fraction of consumers of each of the six groups discussed in Section 4.1.2 is computed by dividing the group's size with the number of consumers who arrive in the same period, e.g., dividing the number of Early-Buy consumers with the number of early consumers. First, we show the case in which early consumers do not expect future discounts, such that $r = 0$. As long as their patience level $\delta < 1$, the utility of waiting to return in Period 2 will never exceed the utility of buying the product now. Figure 4-1 demonstrates that, regardless of the discount level, half of the early consumers either buys the product in Period 1 or exits the store without buying; no early consumer waits for a potential markdown. A steeper discount attracts a larger number of late consumers who opt to buy the discounted product; however, the increased demand cannot make up for the loss in revenue from selling the cheaper product.

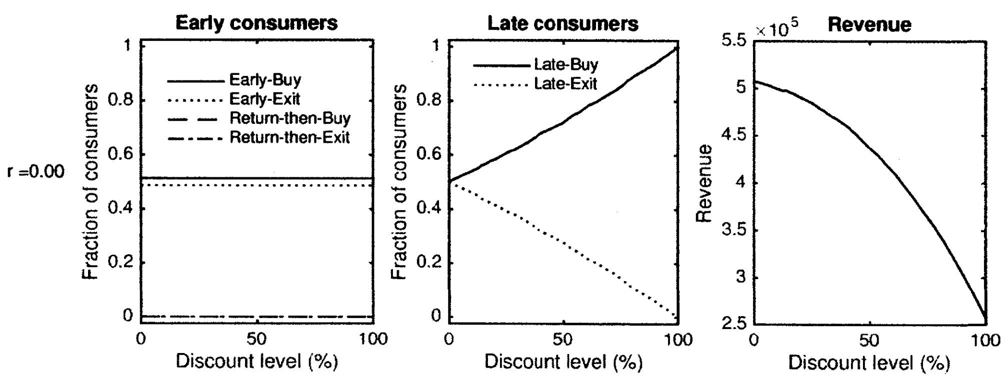


Figure 4-1: Demand and revenue at each discount level when consumers are not expecting discounts

Next, we consider three segments of population: pessimistic, correct, and optimistic about future discounts, which are modeled through $r = 0.75$, 1, and 1.25, respectively. Figures 4-2, 4-3, 4-4 compares how market segmentation and revenue change with the discount level for each of the three types. Across these types, the level of optimism does not affect late consumers' purchase decisions. For pessimistic early consumers, we observe smaller groups of those who buy or exit without buying in Period 1 as the discount is larger. Instead, larger discounts encourage more early consumers to wait for a deal. Every returning consumer buys the discounted product in this case because the realized discount will always be larger than what he expected before (since $r < 1$). The optimal markdown level is 7%, allowing the retailer to earn 1.08% higher revenue compared to when it does not apply any markdown. The market segmentation of early and late consumers and the retailer's revenue by the discount level in this scenario are illustrated in Figure 4-2.

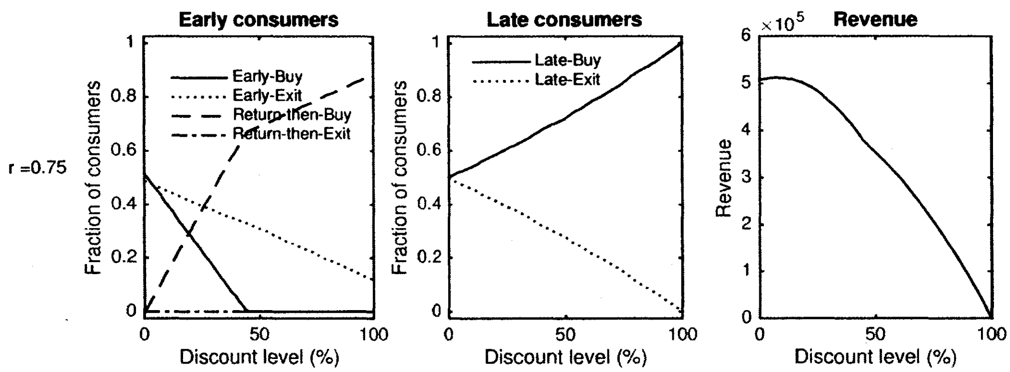


Figure 4-2: Demand and revenue at each discount level when consumers are pessimistic about future discounts

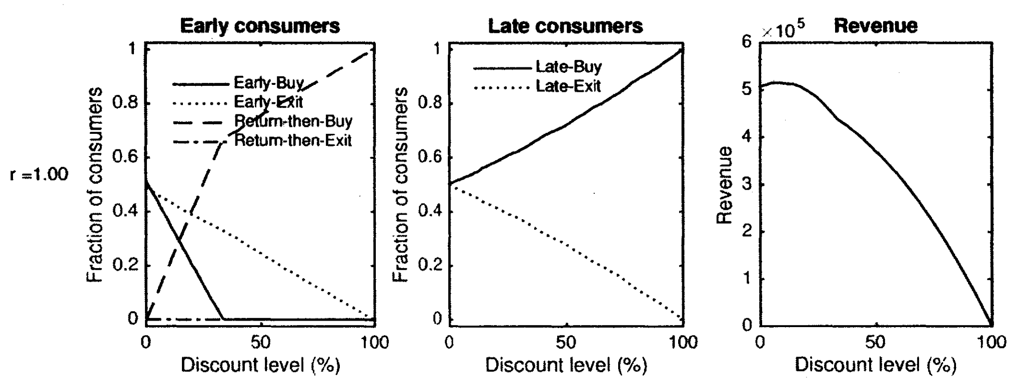


Figure 4-3: Demand and revenue at each discount level when consumers are correct about future discounts

The second segment of consumers are correct about what future discounts will be, meaning that they have more complete information that allows them to make an accurate guess on the level of discount early in the time horizon. Similar dynamics as before are observed here, except that the rate at which early consumers switch from buying or exiting without buying in Period 1 to waiting and buying in Period 2 is

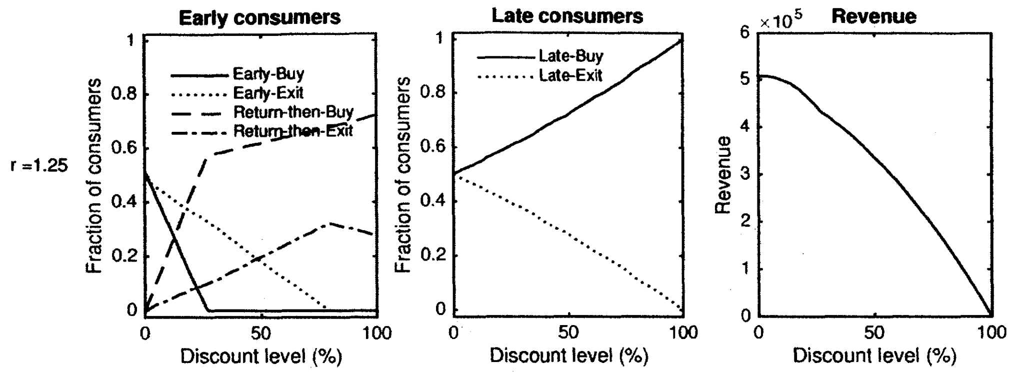


Figure 4-4: Demand and revenue at each discount level when consumers are optimistic about future discounts

faster (e.g., more consumers switch at a lower discount level). There is no gain-loss utility attached to the option to buy a discounted product because the realized discount matches the expectation. The optimal markdown level is 8% in this case and the firm could improve its revenue by 1.64% (see Figure 4-3).

Lastly, for optimistic consumers, we observe a larger fraction of early consumers who decide to wait because their expected discounts are greater than their pessimistic counterparts. However, some of the returning consumers will face loss due to a lower-than-expected realized markdown. As the discount gets steeper, the loss faced by them has a larger impact on their utilities, which in turn lead to a smaller group of returning consumers who end up buying the discounted product. In this case, the firm earns the maximum revenue (0.14% better than using a fixed price) when it applies a 2% markdown in Period 2 (see Figure 4-4).

4.2 The Impact of Model Parameters on Optimal Markdown and Revenue

We numerically compare how much the retailer can improve its revenue by applying an optimal markdown strategy compared to using a fixed pricing (e.g., not applying any discount). The parameters of interest are (i) optimism level (r), (ii) patience level (δ), (iii) distributions of early/late consumers (γ), and (iv) sensitivity to the discount relative to the original price on quality perception (c/a_2). For each of these parameters, we perform a sensitivity analysis of its impact on the optimal markdown level and the revenue improvement for the retailer.

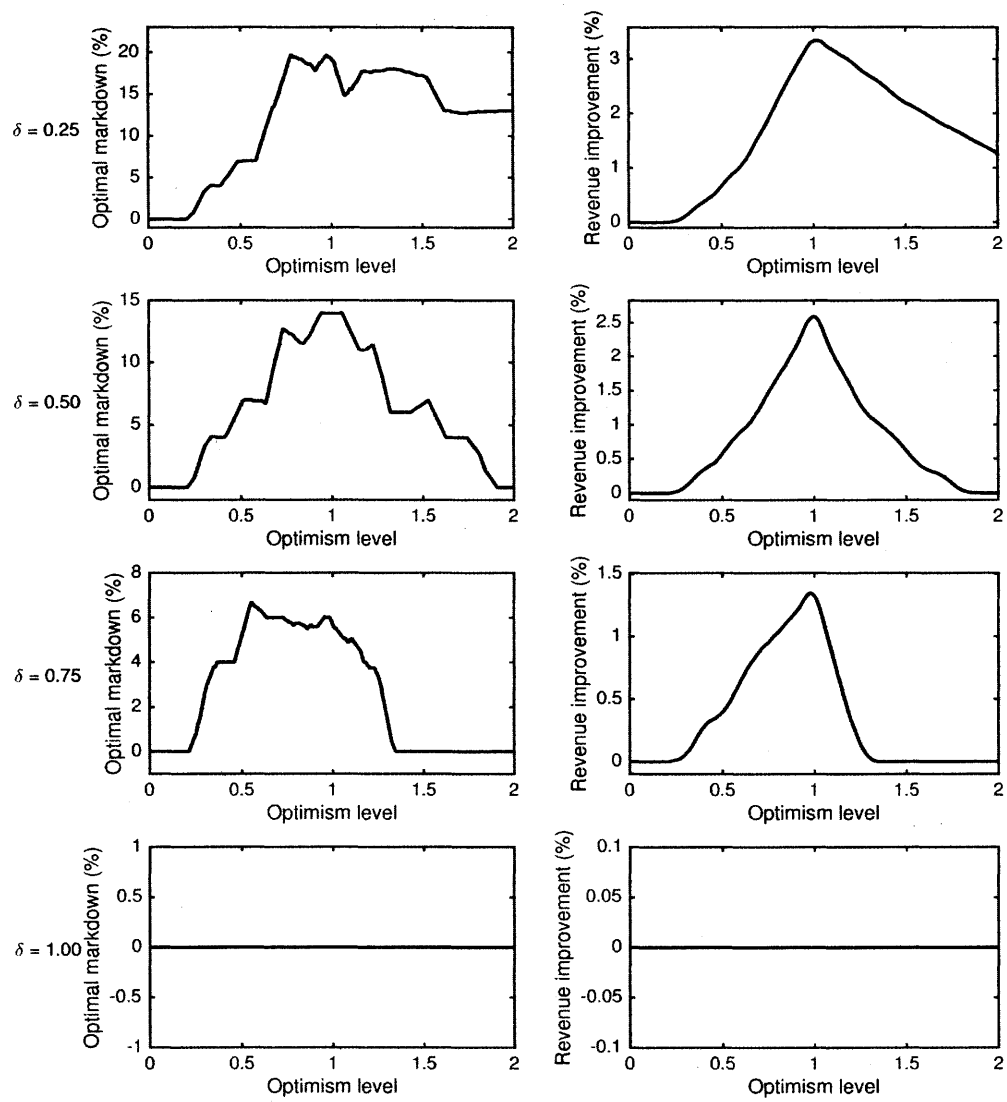


Figure 4-5: Optimal markdown level and revenue improvement by optimism level r

4.2.1 The Impact of Optimism

From the results in 5.4.1, we observe how early consumers' purchase decisions change with the optimism level. In this subsection, we compare the results when r takes values from 0 to 2 and control for the patience level δ to be 0.25, 0.5, 0.75, or 1 and c as 0.4. Figure 4-5 shows that the optimal markdown level and the revenue improvement are largest when $r = 1$, similarly to what we observed earlier. The implication here is that, in order to maximize its revenue, the retailer should make sure that the consumers have perfect information about the future discount, e.g., through pre-announced details about its markdown. The further r is away from 1, the smaller optimal markdown level and revenue improvement are. For optimistic consumers, many of those who return in Period 2 feel a loss when they observe a smaller-than-expected discount and end up not buying. On the other hand, pessimistic early consumers will be more likely to wait and the firm loses the opportunity to sell full-price products to this group. As consumers are more patient (higher δ), the range of optimism level that suggests non-zero optimal markdown becomes smaller. This result is aligned with Theorem 1; larger δ leads to smaller r_2, reducing the range of optimism level that implies nonzero optimal markdown level. When consumers are perfectly patient $\delta = 1$, it is in the retailer's best interest to not apply a markdown strategy. *The retailer should apply a markdown strategy when consumers have a complete information or close expectation about the true amount of the future discount.*

4.2.2 The Impact of Patience

In the previous analysis on optimism, we observed evidence that suggested the importance of patience level. In this section, we further investigate its impact on the optimal markdown and revenue improvement through numerical experiments. The level of optimism is chosen among $r = 0.75$, 1, and 1.25. We find that, from Figure 4-6, a retailer should apply a markdown strategy when its consumers have low patience (small δ). As the consumers become less patient, both the optimal markdown level and the revenue improvement increase. While a deeper discount attracts early consumers, who would otherwise leave the market without buying, to wait for the markdown, consumers with less patient will be more likely to pay the full price for the product right away. In other words, a small δ means that the early consumers value the utility of future purchase less that the options they are currently facing.

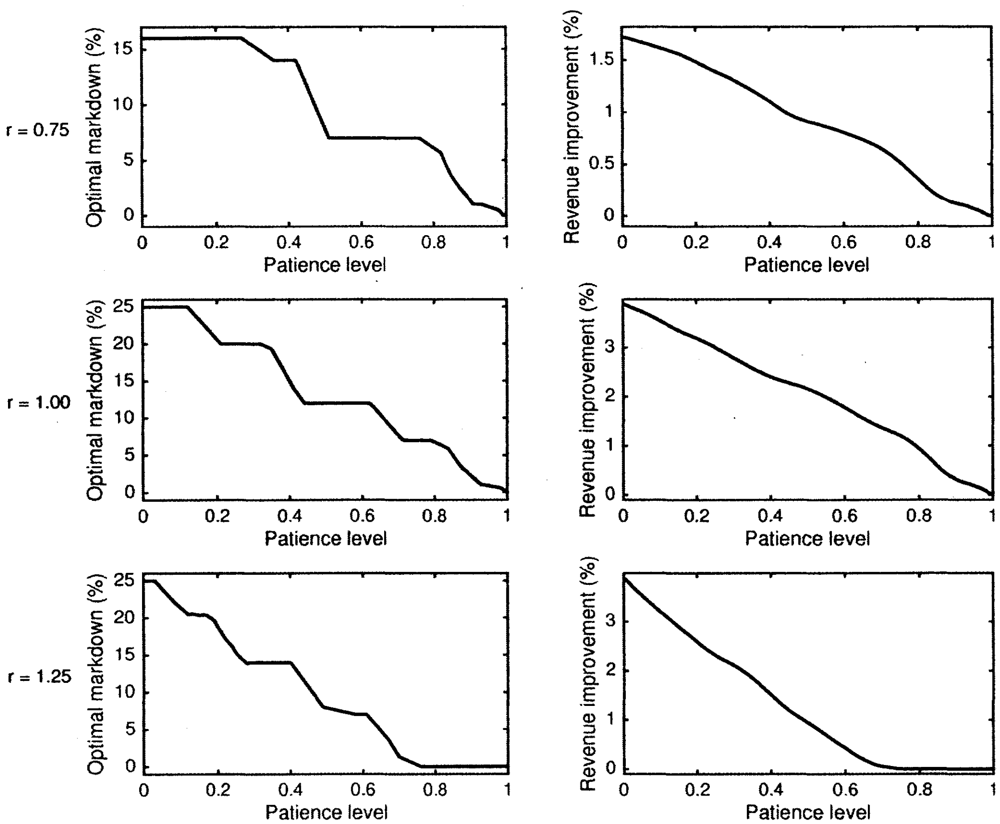


Figure 4-6: Optimal markdown level and revenue improvement by patience level δ

This may be a result of the product's seasonality or innovation that urges them to buy the product right when it is launched. *The retailer should apply a markdown strategy when consumers are less patient and want to own the product early in the season.*

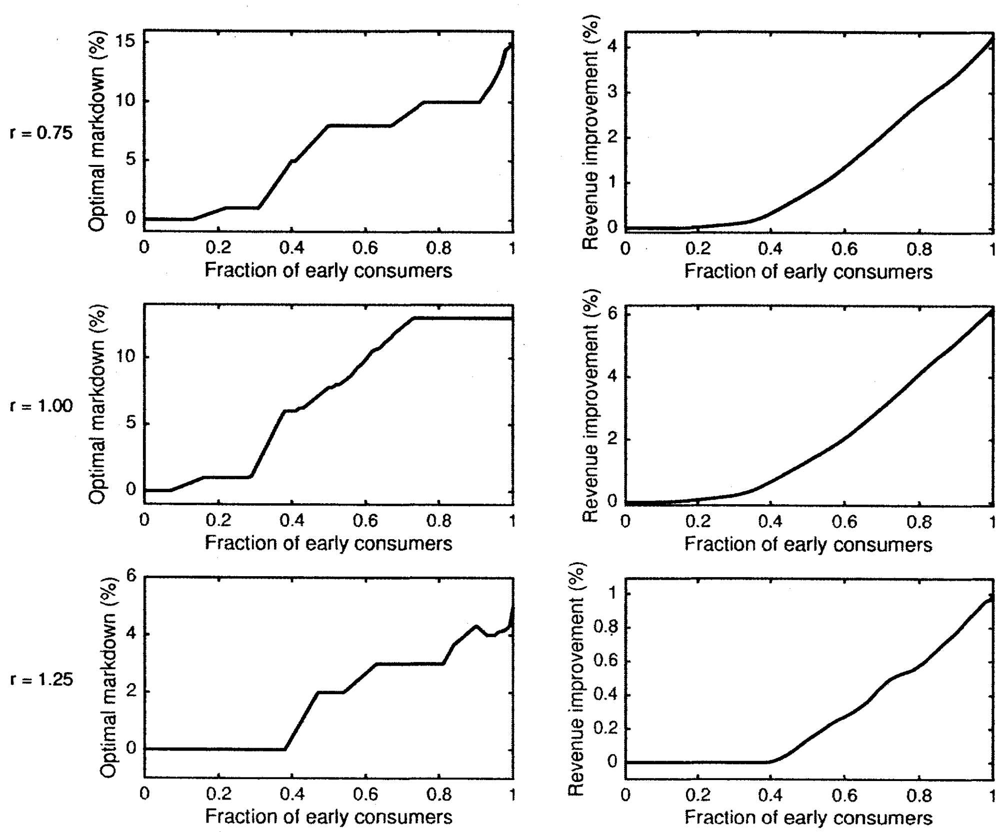


Figure 4-7: Optimal markdown level and revenue improvement by fraction of early consumers γ

4.2.3 The Impact of the Distribution of Arrival Time

We have seen that the benefits of markdown come from the strategic behavior of early consumers. In this part, we fix the patience level to be $\delta = 0.75$ as before, and investigate how the optimal markdown and the revenue are affected by the distribution of early and late consumers in the population, modeled through a parameter γ, i.e., the fraction of consumers who arrive in Period 1. The results from three population with different optimism levels are presented in Figure 4-7. The importance of early consumers is visible, namely: the more consumers arrive early, the more appealing a markdown strategy is. When γ is small, the majority of the population arrive in Period 2 when they have only two available purchase decisions: (i) buying the discounted product or (ii) leave the market without buying. In this case, in order to gain the maximum revenue, the retailer should not apply any discount. In contrast, when γ is large, there is a large group of early consumers who will buy the product at the original price. Then, the retailer can use an appropriate level of markdown to order to attract those who may not buy and make them change their minds. *The retailer should implement a markdown strategy when there is a large fraction of the consumers who visit the store early in the season.*

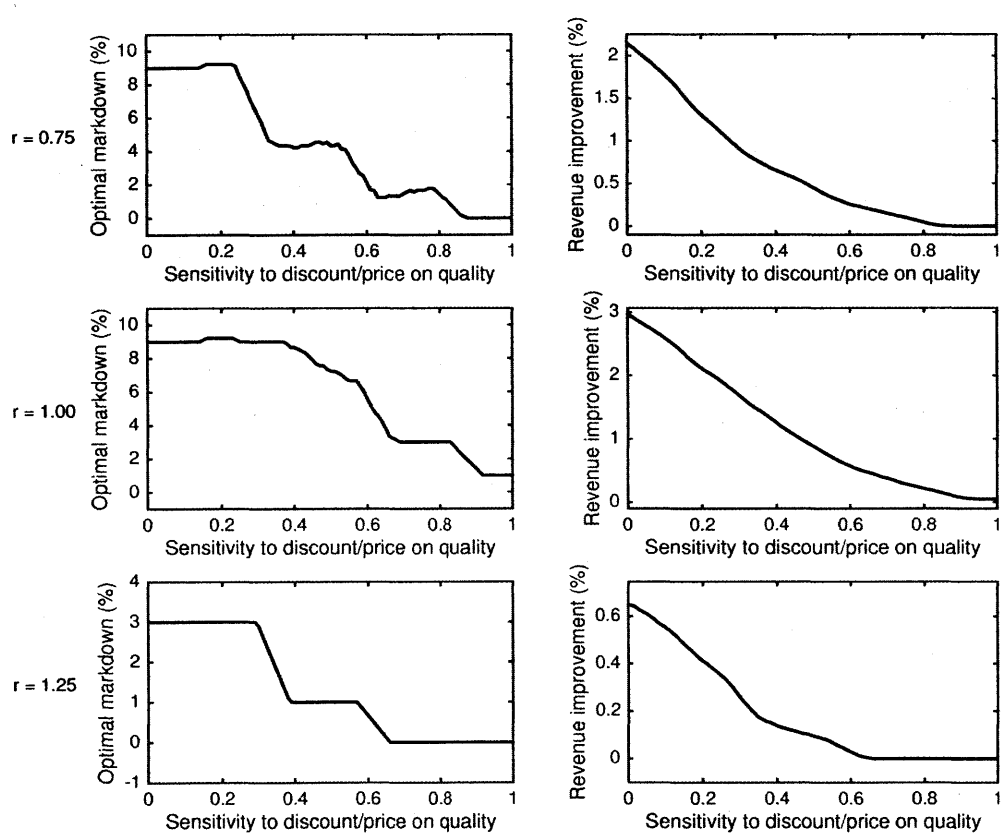


Figure 4-8: Optimal markdown level and revenue improvement by sensitivity to discount/price on quality perception c/a_2

4.2.4 The Impact of Sensitivity to Discount

Lastly, we revisit the first phase of our research when we develop a functional form of the relationship among quality perception, original price, and discount level in Section 4.2.2. We learned from the consumer purchase experiment that only the late consumers use the discount information, in addition to the original price, when they form quality perceptions. Their perceived quality is given by $q_2 = a_2 p - c\Delta$, and from both the experiment and modeling assumptions, $c < a_2$. In this part, we fix a_1 (sensitivity to price on quality for early consumers) and a_2 to be 2, and investigate when c is sampled from a continuous range of $[0, a_2]$. We again compare results from consumers with three levels of optimism as illustrated in Figure 4-8. Across all levels of optimism, a markdown strategy is optimal when c is small, relative to a_2. Since a markdown has a negative impact on the perceived quality, its impact is weaker for consumers with smaller c. They will view a markdown as an encouragement to buy, rather than an inferior product quality. As the consumers are more pessimistic about future discounts (and thus expecting smaller discounts), the negative impact is lessened and the retailer can apply markdown for a wider range of c's. *Therefore, the retailer should apply a markdown strategy when consumers value the original price much higher than the discount when rating the product's quality prior to purchase.*

Chapter 5

Conclusions

This thesis studies the role of quality perception in a consumer demand model and incorporates this aspect in a price optimization for a retailer who sells a single product to a group of consumers over two periods. We perform a consumer purchase experiment that offers new insights into the relationship among the consumers' quality perception, the product's original price, and the discount level, and how such relationship affects their purchase decisions. We find that consumers stick to their original quality perceptions, which they formed when observing the product for the first time. A markdown or discount only affects perceived quality if it is already applied during the consumers' first visit to the market. The data confirm the positive relationship between perceived quality and price that has been documented in the past literature. We further show the different effects of the original price and discount level on quality perception: higher original prices signal higher quality, while deeper discounts suggest lower quality. The impact of the final selling price on quality is, however, found not to be statistically significant. Using a within-subject design, we conclude that quality perception decreases linearly with the discount level. In addition, gender and product categories have interesting impacts on quality. Male consumers make a lower quality rating than female consumers because they perceive a weaker relationship between the original price and quality. Product categories also affect the quality-price relationship, but their impact is not as clear as the gender of the consumers.

Given these empirically-validated insights and other well-established behavioral issues, such as loss aversion and reference-dependent preferences, we propose a refined consumer model where a consumer chooses a purchase option that maximizes his or her utility and may form expectations of future markdowns. We develop a threshold of quality valuation to characterize demand for each option across two periods. Propositions 3.1 and 3.2 provide conditions that determine which option a particular type of consumer would choose. We introduce two additional behavioral factors that play a key role in market segmentation: optimism about future discounts and patience to wait for deals. Then, we analyze the retailer's revenue maximization problem, which optimizes a markdown level for a product with a known original price, when the consumers' quality perceptions are taken into account. As the revenue is a strictly concave function of the discount, Theorem 3.1 states that the firm can earn the maximum revenue if it applies a markdown on the product when the consumers' level of optimism lies in a specific range. Corollary 3.1 is a special case of Theorem 3.1 when the early consumers are extremely patient and have no time preferences. The results from our numerical experiments further provide insights into the impact of different model parameters on the optimal markdown level and the revenue improvement compared to not applying a markdown strategy. We find that the retailer should implement a markdown strategy when consumers (i) are inclined to purchase the product early (or impatient to wait), (ii) consider the product's original price as a stronger quality signal than the discount, or (iii) have a complete information about the markdown level.

We are currently considering an extension of this work in the case where a retailer sells multiple substitutable products under different pricing strategies, including fixed and markdown pricing. We assume that consumers are strategic and compare these options both in terms of price and quality. We also further investigate the situation where consumers make errors in their utility evaluations. Our new model allows the retailer to optimize pricing strategies for a portfolio of products.

Appendix A

Proofs of Theoretical Results

A.1 Proof of Proposition 3.1

Early consumers arrive to the store in Period 1 and observe a product sold at its original price p. We define U_i as the consumers' utility of choosing an option i:

$$U_i = \theta q_i - p_i, \quad i \in \{0, 1, w\},$$

where θ is the *valuation of quality* parameter which is uniformly distributed on [0, θ_{max}], q_i is option i's perceived quality, and p_i is the price of i. U_1 is the utility of purchasing the product at its original price. U_w is the utility of waiting to return in Period 2. The utility of exiting the store without buying is set to be $U_0 = 0$.

Each consumer chooses an option that maximizes his or her utility. Let $X_i(\theta)$ be the indicator function that indicates whether a consumer with valuation of quality θ will choose the option i. Namely:

$$X_i(\theta) = \begin{cases} 1 & \text{if the consumer with } \theta \text{ chooses option i,} \\ 0 & \text{otherwise.} \end{cases}$$

The consumer will choose the option i if and only if $U_i \geq U_j$ for $j \neq i$. Thus:

$$X_i(\theta) = 1 \iff U_i \geq U_j$$

We recall that:

$$U_1(\theta) = \theta a_1 p - p$$

$$U_w(\theta) = \delta(\theta a_1 p - (p - r\Delta))$$

Hence, we can characterize the consumer's purchase decision by evaluating his or her valuation of quality θ. The consumer will purchase the product at the original price if and only if $U_1(\theta) \geq 0$ and $U_1(\theta) \geq U_w(\theta)$; i.e.,

$$\theta \geq \bar{\theta} := \frac{1}{a_1} + \frac{r\Delta\delta}{a_1 p(1-\delta)} \tag{A.1}$$

The consumer will leave the store without buying if and only if $U_1(\theta) \leq 0$ and $U_w(\theta) \leq 0$; i.e.,

$$\theta \leq \underline{\theta} := \frac{1}{a_1} - \frac{r\Delta}{a_1 p} \tag{A.2}$$

The consumer will choose to wait and return in Period 2 if and only if $U_w(\theta) \geq 0$ and $U_w(\theta) \geq U_1(\theta)$; i.e.,

$$\underline{\theta} \leq \theta \leq \bar{\theta} \tag{A.3}$$

For those who choose to return in Period 2, they observe new price information and choose between (i) buying the product with a discount Δ applied, and (ii) exiting without purchasing the product. Recall that the utility of buying the product in Period 2 is given by:

$$U_2(\theta) = \theta a_1 p - (p - \Delta) + \Psi\left(\theta a_1 p - (p - \Delta) - \delta(\theta a_1 p - (p - r\Delta))\right), \tag{A.4}$$

where $\Psi(x)$ reflects the consumer's gain-loss utility:

$$\Psi(x) = \begin{cases} \eta x & x \geq 0 \\ 2\eta x & x \leq 0 \end{cases}$$

The consumer will experience a feeling of gain when $\theta a_1 p - (p - \Delta) - \delta(\theta a_1 p - (p - r\Delta)) \geq 0$, which happens if and only if:

$$\theta \geq \theta_1 := \frac{1}{a_1} - \frac{\Delta(1-\delta r)}{pa_1(1-\delta)}$$

Let

$$\bar{\eta} = \begin{cases} \eta & \theta \geq \theta_1 \\ 2\eta & \theta \leq \theta_1 \end{cases}$$

Then, Equation (A.4) can be rewritten as:

$$U_2(\theta) = \theta a_1 p - (p - \Delta) + \bar{\eta}\left(\theta a_1 p - (p - \Delta) - \delta(\theta a_1 p - (p - r\Delta))\right) \tag{A.5}$$

Hence, returning consumers will purchase the product in Period 2 if and only if $\underline{\theta} \leq \theta \leq \bar{\theta}$ and $U_2(\theta) \geq 0$, i.e.,

$$\left.\begin{aligned} &\underline{\theta} \leq \theta \leq \bar{\theta} \\ &\theta \geq \theta_2(\bar{\eta}) := \frac{1}{a_1} - \frac{\Delta(1+\bar{\eta}(1-\delta r)}{a_1 p(1+\bar{\eta}(1-\delta)))} \end{aligned}\right\} \iff \max\left(\underline{\theta}, \theta_2(\bar{\eta})\right) \leq \theta \leq \bar{\theta} \tag{A.6}$$

We can obtain the following results:

$$\bar{\theta} - \theta_2(\bar{\eta}) = \frac{(1-\delta)(1+\bar{\eta}) + r\delta}{(1-\delta)(1+\bar{\eta}(1-\delta))} \frac{\Delta}{a_1 p} \geq 0,$$

$$\begin{aligned} \underline{\theta} \leq \theta_2(\bar{\eta}) &\iff \frac{1}{a_1} - \frac{r\Delta}{a_1 p} \leq \frac{1}{a_1} - \frac{\Delta(1+\bar{\eta}(1-\delta r)}{a_1 p(1+\bar{\eta}(1-\delta)))} \\ &\iff r \geq 1, \end{aligned}$$

and

$$\theta_1 \geq \theta_2(\bar{\eta}) \iff \frac{1}{a_1} - \frac{\Delta(1-\delta r)}{pa_1(1-\delta)} \geq \frac{1}{a_1} - \frac{\Delta(1+\bar{\eta}(1-\delta r)}{a_1 p(1+\bar{\eta}(1-\delta))}$$
$$\iff r \geq 1$$

There are two separate cases to further investigate:

(a) If $r \geq 1$, then:

- If $\theta \geq \theta_1$, then we set $\bar{\eta} = \eta$, and the early consumer chooses to return in Period 2 and eventually buys the product if and only if $\theta_1 \leq \theta \leq \bar{\theta}$.
- If $\theta \leq \theta_1$, then we set $\bar{\eta} = 2\eta$, and the early consumer chooses to return in Period 2 and eventually buys the product if and only if $\theta_2(2\eta) \leq \theta \leq \theta_1$.

Hence, the early consumer returns in Period 2 and buys the product if and only if $\theta_2(2\eta) \leq \theta \leq \bar{\theta}$. Otherwise, he returns in Period 2 but chooses to exit without purchasing if and only if $\underline{\theta} \leq \theta \leq \theta_2(2\eta)$.

(b) If $r \leq 1$, then $\underline{\theta} \leq \theta_2(\bar{\eta})$ and the early consumer waits and returns to purchase the product if and only if $\underline{\theta} \leq \theta \leq \bar{\theta}$. In fact, every returning consumers will buy the product.

A.2 Proof of Proposition 3.2

Late consumers arrive in Period 2 and can either purchase the product or exit without purchasing. Their utility of purchasing the product is given by:

$$U_2^2(\theta) = \theta(a_2 p - c\Delta) - (p - \Delta)$$

The late consumer purchases the product if and only if $U_2^2(\theta) \geq 0$, i.e.,

$$\theta \geq \tilde{\theta} := \frac{p-\Delta}{a_2 p - c\Delta}$$

A.3 Proof of Lemma 3.1

(i) For a consumer with a valuation of quality θ, we denote the following indicator functions based on his arrival time to the store and θ:

- If he arrives in Period 1,
  - whether he purchases the product: $X_1(\theta) = \mathbb{1}_{\theta\in[\bar{\theta},\theta_{max}]}$
  - whether he waits for a potential markdown, returns, and buys the product in Period 2:

$$X_2(\theta) = \begin{cases} \mathbb{1}_{\theta\in[\theta_2(2\eta),\bar{\theta}]} & r \geq 1 \\ \mathbb{1}_{\theta\in[\underline{\theta},\bar{\theta}]} & r \leq 1 \end{cases}$$

- If he arrives in Period 2, whether he purchases the product:

$$X_3(\theta) = \mathbb{1}_{\theta\in\left[\frac{p-\Delta}{a_2 p - c\Delta},\theta_{max}\right]}$$

The aggregated demand for each option i over all consumers is given by $D_i = \mathbb{E}_\theta[X_i(\theta)]$, Individual consumer valuation of quality is distributed uniformly over $[0,\theta_{max}]$, thus:

$$D_1 = \theta_{max} - \bar{\theta}$$

$$D_2 = \begin{cases} \bar{\theta} - \theta_2(2\eta) & r \geq 1 \\ \bar{\theta} - \underline{\theta} & r \leq 1 \end{cases}$$

$$D_3 = \theta_{max} - \tilde{\theta}$$

(ii)
- $D_1 = (\theta_{max} - \frac{1}{a_1} - \frac{r\delta\Delta}{a_1 p(1-\delta)})$ is linear and decreasing in Δ, r, δ.
- $D_2 = \begin{cases} \Delta\dfrac{r\delta + (1-\delta)(1+2\eta)}{(1-\delta)(1+2\eta(1-\delta))pa_1}, & r \geq 1 \\ \Delta\dfrac{r}{a_1 p(1-\delta)a_1}, & r \leq 1 \end{cases}$ is linear and increasing in Δ, r, δ.

- $D_3 = \theta_{max} - \dfrac{p-\Delta}{a_2 p - c\Delta}$ is hyperbolic and increasing in Δ.

A.4 Proof of Theorem 3.1

The objective is to maximize:

$$
\begin{aligned}
Rev(\Delta) &= \gamma[pD_1 + (p-\Delta)D_2] + (1-\gamma)(p-\Delta)D_3 \\
&= \begin{cases}
\gamma p(\theta_{max} - \bar{\theta}) + \gamma(p-\Delta)(\bar{\theta} - \theta_2(2\eta)) & r \geq 1 \\
\quad + (1-\gamma)(p-\Delta)\left(\theta_{max} - \dfrac{p-\Delta}{a_2 p - c\Delta}\right), & \\
\gamma p\left(\theta_{max} - \bar{\theta}\right) & r \leq 1 \\
\quad + \gamma(p-\Delta)(\bar{\theta} - \underline{\theta}) + (1-\gamma)(p-\Delta)\left(\theta_{max} - \dfrac{p-\Delta}{a_2 p - c\Delta}\right), &
\end{cases} \\
&= \begin{cases}
p\gamma\left(\theta_{max} - \dfrac{1}{a_1} - \dfrac{r\delta\Delta}{a_1 p(1-\delta)}\right) & \\
\quad + \gamma(p-\Delta)\Delta \dfrac{r\delta + (1-\delta)(1+2\eta)}{(1-\delta)(1+2\eta(1-\delta))pa_1} & r \geq 1 \\
\quad + (1-\gamma)(p-\Delta)\left(\theta_{max} - \dfrac{p-\Delta}{a_2 p - c\Delta}\right), & \\
p\gamma\left(\theta_{max} - \dfrac{1}{a_1} - \dfrac{r\delta\Delta}{a_1 p(1-\delta)}\right) & \\
\quad + \gamma(p-\Delta)\Delta \dfrac{r}{a_1 p(1-\delta)a_1} & r \leq 1 \\
\quad + (1-\gamma)(p-\Delta)\left(\theta_{max} - \dfrac{p-\Delta}{a_2 p - c\Delta}\right), &
\end{cases}
\end{aligned}
$$

We can write the objective as a sum of three functions f, g and h, namely:

$$Rev(\Delta) = f(\Delta) + g(\Delta) + h(\Delta),$$

where

$$
\begin{aligned}
f(\Delta) &= \gamma p\left(\theta_{max} - \frac{1}{a_1} - \frac{r\delta\Delta}{a_1 p(1-\delta)}\right) + (1-\gamma)(p-\Delta)\theta_{max} \\
g(\Delta) &= \begin{cases} \gamma(p-\Delta)\Delta\dfrac{r\delta + (1-\delta)(1+2\eta)}{(1-\delta)(1+2\eta(1-\delta))pa_1}, & r \geq 1 \\ \gamma(p-\Delta)\Delta\dfrac{r}{a_1 p(1-\delta)}, & r \leq 1 \end{cases} \\
h(\Delta) &= -(1-\gamma)\frac{(p-\Delta)^2}{a_2 p - c\Delta}
\end{aligned}
$$

Since $h^{''}(\Delta) = -2(1-\gamma)\dfrac{p^2(c-a_2)^2}{(a_2 p - c\Delta)^3} \leq 0$, we have that h is concave. f is linear and g is concave quadratic, which proves that $Rev(\Delta)$ is strictly concave in Δ and there is a unique optimal solution to the revenue maximization problem, that is, a unique optimal markdown level, Δ_{opt}.

Substituting $\Delta = \Delta_{opt}$ in the objective's first-order condition, we obtain:

$$
\begin{aligned}
\text{Rev}^{'}(\Delta_{opt}) = 0 &\iff f^{'}(\Delta_{opt}) + g^{'}(\Delta_{opt)} + h^{'}(\Delta_{opt}) = 0 \\
&\iff \begin{cases} \dfrac{-\gamma r\delta}{a_1(1-\delta)} + \gamma\dfrac{r\delta + (1-\delta)(1+2\eta)(p-2\Delta_{opt}}{(1-\delta)(1+2\eta(1-\delta))a_1 p} & r \geq 1 \\ \quad +(1-\gamma)\left(2\dfrac{(p-\Delta_{opt})}{a_2 p - c\Delta_{opt}} - c(\dfrac{p-\Delta_{opt}}{a_2 p - c\Delta_{opt}})^2\right) = 0, & \\ \dfrac{-\gamma r\delta}{a_1(1-\delta)} + \gamma\dfrac{r(p-2\Delta_{opt})}{a_1 p(1-\delta)} & r < 1 \\ \quad +(1-\gamma)\left(2\dfrac{(p-\Delta_{opt})}{a_2 p - c\Delta_{opt}} - c(\dfrac{p-\Delta_{opt}}{a_2 p - c\Delta_{opt}})^2\right) = 0, & \end{cases}
\end{aligned}
$$

For the optimal markdown to be positive,

$$
\begin{aligned}
\Delta_{opt} > 0 &\iff Rev'(0) > 0 \\
&\iff \begin{cases} \dfrac{-\gamma r\delta}{a_1(1-\delta)} - (1-\gamma)\theta_{max} + \gamma\dfrac{r\delta + (1-\delta)(1+2\eta)}{(1-\delta)(1+2\eta(1-\delta))a_1} & r \geq 1 \\ \quad +(1-\gamma)\left(\dfrac{2}{a_2} - \dfrac{c}{a_2^2}\right) > 0, & \\ \dfrac{-\gamma r\delta}{a_1(1-\delta)} - (1-\gamma)\theta_{max} & r \leq 1 \\ \quad +\gamma\dfrac{r}{a_1(1-\delta)} + (1-\gamma)\left(\dfrac{2}{a_2} - \dfrac{c}{a_2^2}\right) > 0, & \end{cases} \\
&\iff \begin{cases} \dfrac{1+2\eta(1-r\delta)}{1+2\eta(1-\delta)} > T, & r \geq 1 \\ r > T, & r \leq 1 \end{cases} \\
&\iff \begin{cases} r < T + \dfrac{1+2\eta(1-T)}{2\eta\delta}, & r \geq 1 \\ r > T, & r \leq 1, \end{cases}
\end{aligned}
$$

where

$$T := \frac{1-\gamma}{\gamma} a_1 \left(\frac{2}{a_2} - \frac{c}{a_2^2} + \theta_{max}\right)$$

Thus,

- If $T > 1$, then $\Delta_{opt} > 0 \iff r \in (1, T)$
- If $T \leq 1$, then $\Delta_{opt} > 0 \iff r \in (T, T + \dfrac{1+2\eta(1-T)}{2\eta\delta})$

Denote:

$$r_1 = \min(1, T)$$

$$r_2 = \max\left(T, T + \frac{1+2\eta(1-T)}{2\eta\delta}\right)$$

We conclude that the firm should apply a (non-zero) markdown on its product,

$$\Delta_{opt} > 0 \iff r \in (r_1, r_2)$$

Appendix B

Details of Consumer Purchase Experiment

B.1 Study 1

B.1.1 Example Survey Questions:

We implemented Study 1 on the Qualtrics[1] platform and recruited participants from Amazon Mechanical Turk. The participants must meet the following qualifications: (i) reside in the United States, (ii) have been approved for at least 1000 HITs[2], and (iii) have HIT Approval Rate of at least 99% for all of our past HITs. Below, we present the screenshots of information and questions shown to 13 male participants, who were randomly assigned into one of the 24 experimental conditions, such that: $ArrivalTime =$ "early", $OriginalPrice = \$35$, and $Discount = 0$.

[1] Qualtrics is a large research company based in the US that conducts quantitative and qualitative research studies (Snow and Mann 2013)

[2] A HIT, or Human Intelligence Task, represents a single, self-contained task that an Amazon Mechanical Turk Worker can work on, submit an answer, and collect a reward for completing.

Welcome!

Thank you for your participation. Please read the following instructions carefully.

- Note that there are no right or wrong answers.
- Please do not press the back button in your browser while answering the survey! It will terminate the survey and you will not receive the completion code. Please enable Javascript on your browser to take this survey.

Before we begin, please verify that the ID in the field below is your correct Amazon Mechanical Turk ID.

- If it is your ID, please click on Next.
- If it is not your ID, or if no ID is displayed, please enter your ID and click on Next.

Figure B-1: Landing page

Consent to Participate

Before continuing, please read the following:

- Our goal in this survey is to understand people's preferences among different alternatives.
- Throughout the survey, you will be asked to answer questions about your choices, attitudes, and experience.
- Your participation is voluntary. You may decline to answer any or all of the questions at any time. However, by doing so, you will not be eligible to receive any payments.
- To withdraw, simply close your browser.
- All survey information will be retained and hosted on a third party (Qualtrics) server and not on an MIT server.
- This survey is confidential. You will not be asked to enter any information that can be traced back to your identity. All data will be reported only at an aggregate level.
- There are no anticipated potential risks from taking this survey.

If you have any questions regarding this survey, you may contact us at MITPQResearch@gmail.com.

I AGREE to participate in this survey.

I DECLINE to participate in this survey.

Before we start, please select your gender.

Male	Female

Figure B-2: Consent form and gender question

Part 1 of 2

You will be presented with a shopping scenario where you are looking to purchase a new fashion item. Then, you will be asked to rate the product's quality on a 0 to 100 point scale and choose one of the purchase options.

Quality rating:

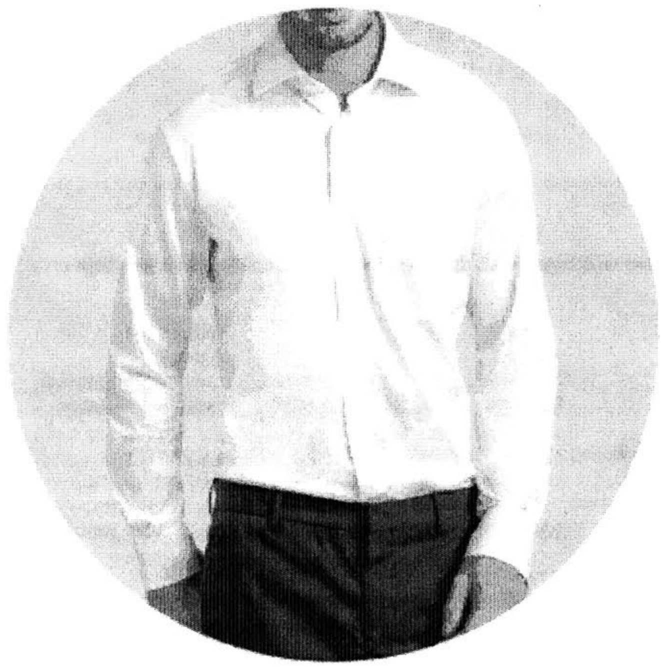
- A higher number means you think the product is likely to have a higher quality.
- For example, 0 means you think the product is likely to have very low quality, while 100 means you think the product is likely to have very high quality.

Note that you will not be asked to actually purchase any of these products.

Figure B-3: Description of Part 1

Shopping Scenario: Buying a Shirt

You are looking for a new shirt, and you have found the following option.



Shirt A

- Currently listed original price: \$35.00
- It may be marked down to a lower price in three months.
- Its price will never go up, and availability is guaranteed even at markdown.

- 100% cotton. Available in multiple colors.
- This shirt is machine washable for easy care.
- Stay polished and professional effortlessly with new wrinkle free technology.

Figure B-4: Product information for early consumers

Quality Rating

State below your quality rating for **this shirt** on a scale from 0 to 100:

- A higher number means you think the product is likely to have a higher quality.
- For example, 0 means you think the product is likely to have very low quality, while 100 means you think the product is likely to have very high quality.

Likely to have very low quality — Likely to have very high quality

0 10 20 30 40 50 60 70 80 90 100

Quality rating

State how much you agree or disagree with the following statements regarding **this shirt**:

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
My family and friends will likely agree that I should buy this shirt at this price.	○	○	○	○	○	○	○
I am willing to pay $35.00 for this shirt.	○	○	○	○	○	○	○
This shirt contains the features that I want.	○	○	○	○	○	○	○
Shirts sold at $35.00 are often NOT reliable.	○	○	○	○	○	○	○
Judging from the price $35.00, this shirt is likely to have a good quality.	○	○	○	○	○	○	○

Expected Discount

How much discount (in % off from the original price) do you expect to see applied on **this shirt** in the next three months?

Expected discount (% off)

0 10 20 30 40 50 60 70 80 90 100

Figure B-5: Questions following the product description for early consumers

Purchase Decision

Please make your purchase decision by selecting one of the choices below:

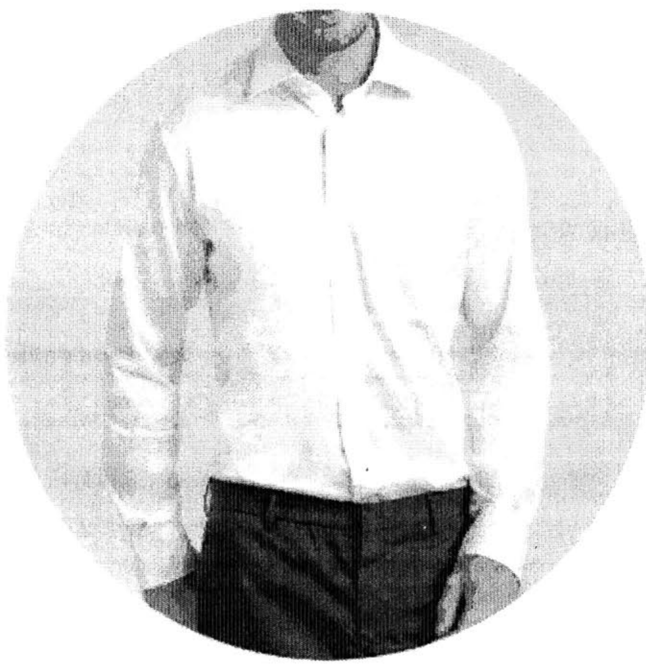
Buy this shirt now.	Wait for potential markdown on this shirt and come back in three months.	Exit without buying the shirt.

Please explain why you decided **NOT** to buy this shirt now but to wait for a potential markdown.

Figure B-6: Questions on purchase decision and reasons behind such decision

Shopping Scenario (cont.): Buying a Shirt

You have previously chosen to wait for a potential markdown on the following shirt. After three months have passed, you have returned to the store and found the same shirt is still available. However, the store did not apply any markdown on it.



Shirt A

- Price: $35.00
- The store did not apply any markdown.
- There will be no more markdowns in the future.

- 100% cotton. Available in multiple colors.
- This shirt is machine washable for easy care.
- Stay polished and professional effortlessly with new wrinkle free technology.

Figure B-7: Product description for returning consumers

You rated the quality of **this shirt** to be **80 out of 100** when it was offered at **the original price** three months ago.

Given the new information, does your quality rating now change compared to what you stated before?

Yes	No

Quality Rating

State below your quality rating of **this shirt** at the current price on a scale from 0 to 100:

- A higher number means you think the product is likely to have a higher quality.
- For example, 0 means you think the product is likely to have very low quality, while 100 means you think the product is likely to have very high quality.

Likely to have very low quality — Likely to have very high quality

0 10 20 30 40 50 60 70 80 90 100

Quality rating

State how much you agree or disagree with the following statements regarding this shirt at the current marked down price:

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Please select Strongly Disagree for this statement.	○	○	○	○	○	○	○
My family and friends will likely agree that I should buy this shirt now.	○	○	○	○	○	○	○

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I am willing to pay $35.00 for this shirt.	○	○	○	○	○	○	○

Figure B-8: Questions about quality perception and value if a returning participant reports that quality has changed

Purchase Decision

Please make your purchase decision by selecting one of the choices below:

Buy this shirt at this price.

Exit without buying the shirt.

Please explain why you decided to buy this shirt.

Figure B-9: Questions on purchase decision and reasons behind such decision

Part 2 of 2

Shirts in General

Think about your experience with buying shirts in general. Please state how much you agree or disagree with the following statements:

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I do not like buying shirts at full price.	○	○	○	○	○	○	○
My quality perception of a shirt prior to purchase is usually consistent with my experience when using it.	○	○	○	○	○	○	○
I am familiar with or knowledgeable about shirts.	○	○	○	○	○	○	○
I expect to see discounts on shirts.	○	○	○	○	○	○	○
Quality is an important factor to consider when I shop for shirts.	○	○	○	○	○	○	○

Figure B-10: Part 2: Questions on general shopping experiences

Pricing Strategies and Quality

There are two common pricing strategies in the market

- Fixed Pricing: The price of a product never changes.
- Markdown Strategy: The price of a product may be discounted to a lower price, and it will never go back up.

- Consider a shirt sold at a discount (markdown)

State how much you agree or disagree with the following statements regarding your quality rating of this shirt under discount:

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree	This factor does not affect my quality rating
The higher the original price of this shirt, the more I think that this shirt is of LOWER quality.	○	○	○	○	○	○	○	○
If the final price of this shirt is higher than typical prices of comparable shirts, the more I think this shirt is of HIGHER quality.	○	○	○	○	○	○	○	○
If the original price of this shirt is higher than typical prices of comparable shirts, the more I think this shirt is of HIGHER quality.	○	○	○	○	○	○	○	○
The higher the final price of this shirt, the more I think that this shirt is of HIGHER quality.	○	○	○	○	○	○	○	○
Products sold under fixed pricing usually have a HIGHER quality than products sold under a markdown strategy	○	○	○	○	○	○	○	○
Please select Strongly Disagree for this statement.	○	○	○	○	○	○	○	○
The deeper the discount of this shirt, the more I think that this shirt is of HIGHER quality.	○	○	○	○	○	○	○	○

Figure B-11: Part 2: Questions on general shopping experiences

Quality Ratings

On a scale from 0 to 100:

- A higher number means you think the shirt is likely to have a higher quality.
- For example, 0 means you think the shirt is likely to have very low quality, while 100 means you think the shirt is likely to have very high quality.

We ask for **two numbers, A and B,** between 0 and 100 such that:

- For a shirt that you think has **good quality**, you will never rate it below the number **A**. What would that number A be?
- For a shirt that you think has **bad quality**, you will never rate it above the number **B**. What would that number B be?

Likely to have very low quality									Likely to have very high quality	
0	10	20	30	40	50	60	70	80	90	100

For a shirt that you think has **good quality**, you will never rate it below the number A. What would that number A be?

For a shirt that you think has **bad quality**, you will never rate it above the number B. What would that number B be?

Common Price for Shirts

Based on your experience, what is **the original price** you usually see for new shirts similar to the ones shown. **The original price is the price of a shirt when it is a New Arrival item.**

Common Discount for Shirts

Based on your experience, what is **the % off discount** you usually see applied on shirts similar to the ones shown.

0	10	20	30	40	50	60	70	80	90	100

Common discount applied on shirts (% off)

Figure B-12: Part 2: Questions on quality ratings and common price/discount for similar products

Next, we list alternative descriptions presented to the participants who were assigned to other experimental conditions. For returning consumers who were assigned to a condition with a non-zero discount level:

> You have previously chosen to wait for a potential markdown on the following shirt. After three months have passed, you have returned to the store and found the same shirt is available at a discounted price:
>
> - Price: \$X
> - Y% off from the original price: \$35.00
> - There will be no more markdowns in the future.

For late consumers who were assigned to a condition with no markdowns:

> You are looking for a new shirt and you have found the following option sold at a store that applies markdown on some of its products.
>
> - Price: \$35.00
> - It was sold at this same price three months ago.
> - The store did not apply any markdown.
> - There will be no more markdowns in the future.

Lastly, for late consumers who were assigned to a condition with a non-zero discount level:

> You are looking for a new shirt and you have found the following option sold at a store that applies markdown on some of its products.
>
> - Price: \$X
> - Y% off from the original price: \$35.00 three months ago.
> - There will be no more markdowns in the future.

B.1.2 Composite Perceived Value:

For each participant in each period, we compute an average of his or her agreement to each of the five statements regarding perceived value, where 1 represents "strongly disagree" and 7 represents "strongly agree". While the higher level of agreement reflects a higher value, one of the statements is presented in an opposite direction and has to be reversed to the same framework as the the rest, i.e., Strongly disagreeing (1) to "Products sold at this price are often NOT reliable" is converted to strongly agreeing (7) to "Products sold at this price are often reliable." Lastly, we scale the 1-7 score to 0-1 *perceived value.* We·also compute a *perceived value of quality* by averaging and scaling the responses to two statements related to the product quality: "Judging from the price, this product is likely to have a good quality." and the reverse of "Products sold at this price are often NOT reliable".

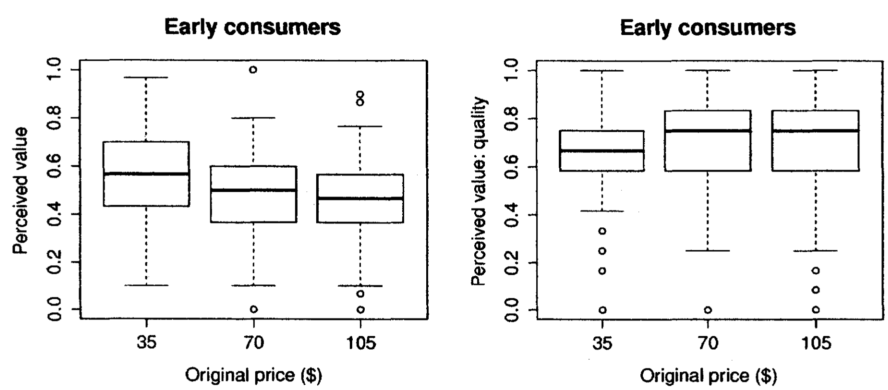


Figure B-13: Perceived value and perceived value of quality for early consumers

For early consumers (see Figures B-13), we observe that perceived value in Period 1 decreases with a higher original price, while perceived value of quality increases with the original price. This result convinces us that some participants frame "quality" as value during the consumer survey experiment. Figure B-14 shows that returning consumers do not update either their perceived value nor perceived value of quality, in the same manner with their fixed quality perception we observed earlier.

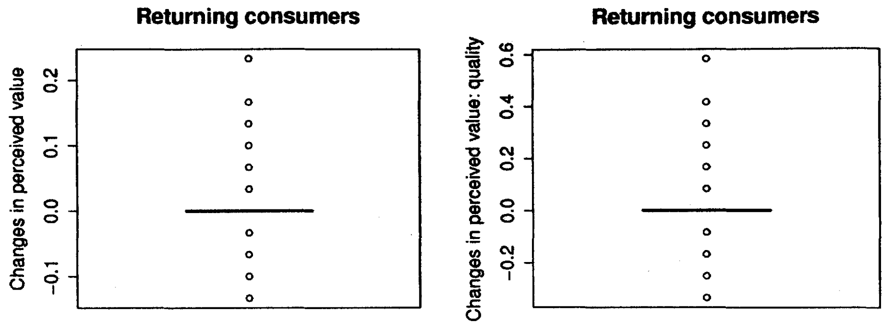


Figure B-14: Changes in perceived value and perceived value of quality for returning consumers

Lastly, for late consumers, the relationship between perceived value of quality and the price information is the same as the relationship between perceived quality and price. However, price and discount impact the perceive value in a completely opposite direction (see Figure B-15). This suggests that, when we observed the two opposite patterns of the quality-price relationship in Study 1 (and also Study 2), participants who reported a positive relationship may view "quality" as the product's quality, while those who reported a negative relationship may interpret it as the satisfaction of the offer.

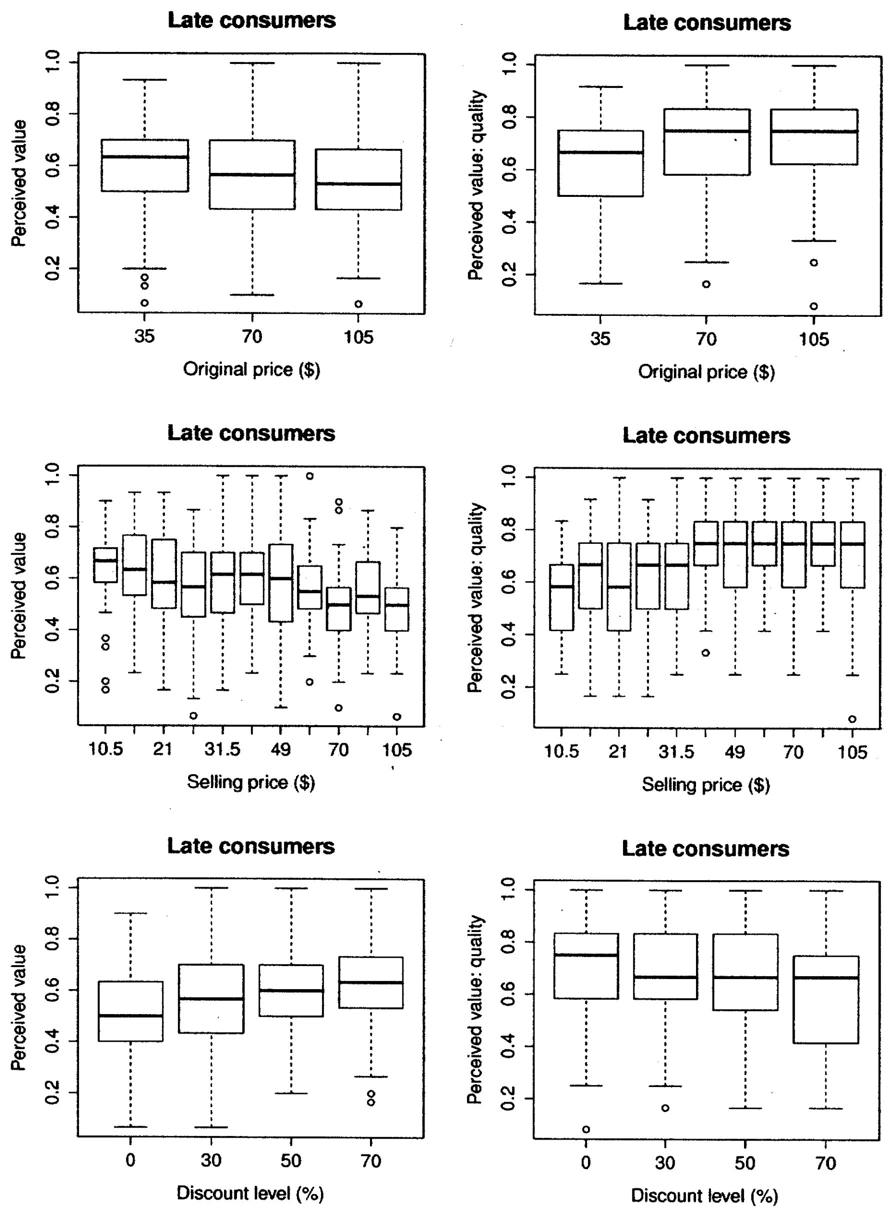


Figure B-15: Perceived value and perceived value of quality for late consumers by different parameters

B.2 Study 2

B.2.1 Example Survey Questions:

Similar to Study 1, Study 2 was implemented on Qualtrics and distributed to the EMBA students to participate online. We present the screenshots of information and questions shown to 35 participants, who were randomly assigned to rate an HDTV in the hi-tech product category.

Part I

In this part, you will be presented with several different products at different prices. For each product at each price, you will be asked your rating of the product's quality on a 0-100 point scale, with a lower number meaning lower quality. You will also be asked whether you will buy the product at the given price.

Note that you will not be asked to actually purchase any of these products.

Figure B-16: Introduction to Part 1 of the study

You are looking for a **new high-definition television (HDTV)** and the one that you like has a price of **$999.99**.

The following information is included in the price tag.

- 48-inch HDTV
- Clear Motion Rate: 240 Hz
- Resolution: 1080p
- Display: LED (Edge-Lit), Wide Color Enhancer
- Eco Sensor, adapting picture and adjusting brightness according to the intensity of light in the room.
- Smart Apps including YouTube, NetFlix, and Hulu Plus.

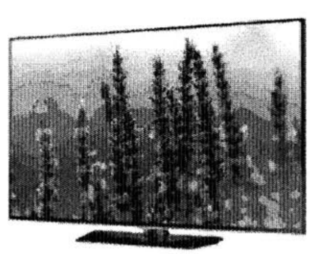
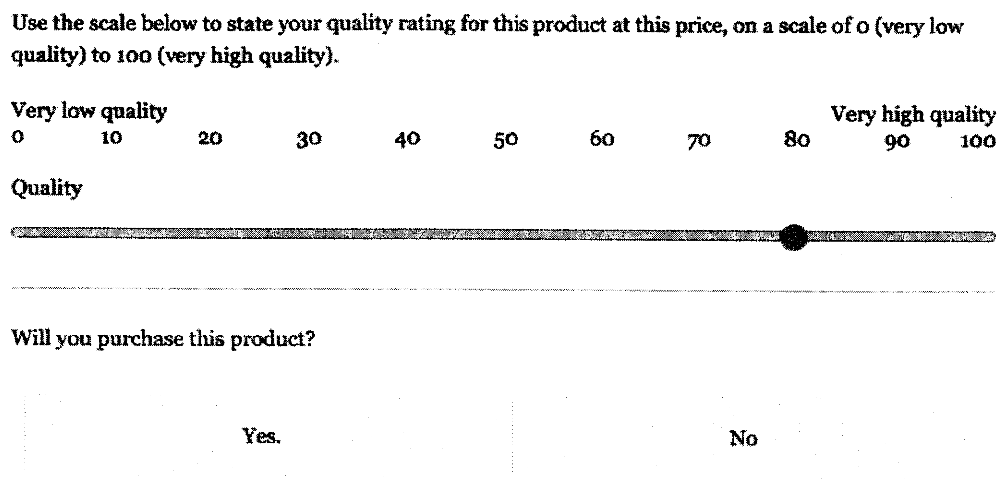


Figure B-17: Product description


Use the scale below to state your quality rating for this product at this price, on a scale of 0 (very low quality) to 100 (very high quality).

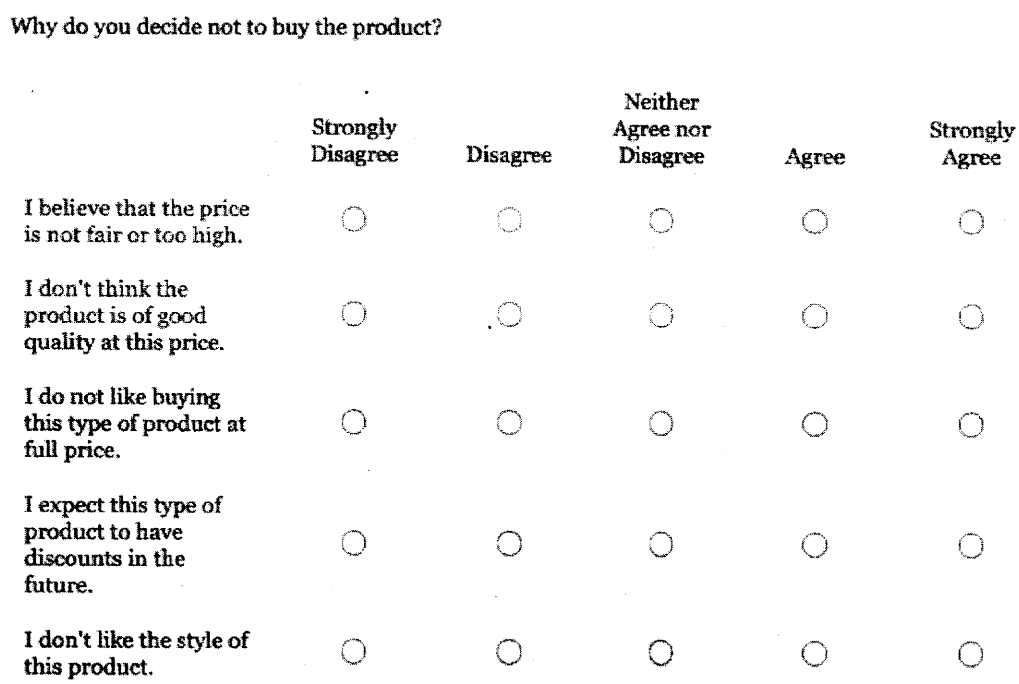
Very low quality | Very high quality
0 10 20 30 40 50 60 70 80 90 100

Quality

Will you purchase this product?

Yes. No

Figure B-18: Quality rating and purchase decision


Why do you decide not to buy the product?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I believe that the price is not fair or too high.					
I don't think the product is of good quality at this price.					
I do not like buying this type of product at full price.					
I expect this type of product to have discounts in the future.					
I don't like the style of this product.					

Figure B-19: Additional questions shown to a participants who chooses not to buy the product

Now the exact same HDTV is sold at a **10% discount.** State below your quality rating of the product at the new price and whether or not you would want to buy the product at the new price.

At the regular price of **$999.99**, you rated the **quality as 80** out of 100.

	Your quality rating On a scale of 0 (very low quality) to 100 (very high quality)	Would you want to buy the product at this price? Yes	 No
At 10% discount		○	○

Figure B-20: Quality rating and purchase decision when a very small discount is applied

Now the exact same HDTV is sold at a **50% discount.** State below your quality rating of the product at the new price and whether or not you would want to buy the product at the new price.

At the regular price of $999.99, you rated the quality as 80 out of 100.

	Your quality rating On a scale of 0 (very low quality) to 100 (very high quality)	Would you want to buy the product at this price? Yes	 No
At 50% discount		○	○

Figure B-21: Quality rating and purchase decision when a large discount is applied

Now the exact same HDTV is sold at a **30% discount.** State below your quality rating of the product at the new price and whether or not you would want to buy the product at the new price.

At the regular price of $999.99, you rated the quality as 80 out of 100.

	Your quality rating On a scale of 0 (very low quality) to 100 (very high quality)	Would you want to buy the product at this price? Yes	 No
At 30% discount		○	○

Figure B-22: Quality rating and purchase decision when a small discount is applied

Now the exact same HDTV is sold at a **60% discount.** State below your quality rating of the product at the new price and whether or not you would want to buy the product at the new price.

At the regular price of $999.99, you rated the quality as 80 out of 100.

	Your quality rating	Would you want to buy the product at this price?	
	On a scale of 0 (very low quality) to 100 (very high quality)	Yes	No
At 60% discount		○	○

Figure B-23: Quality rating and purchase decision when a very large discount is applied

Have you purchased a similar product recently?

Yes No

Regarding your recent purchase of a similar product: a HDTV

Was there a discount on the product you bought?

Yes No

Regarding your recent purchase of a similar product: a HDTV

How much was it?

How much % discount did you get (0-100 off)?

On a scale of 0 (very low quality) to 100 (very high quality), what was your quality rating of the product you bought?

Very low quality Very high quality

0 10 20 30 40 50 60 70 80 90 100

Quality

Figure B-24: Experience with purchasing a similar product. The specific questions are shown only if the participant answers "Yes" to the first question.

Please state how much you agree or disagree with the following statements regarding the product: a HDTV

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am familiar with/knowledgeable about this type of product.					
Quality is an important factor to consider when I shop for this type of product.					
My perception of quality before purchase often matches with my actual experience with this type of product.					

Figure B-25: General questions about the particular product category

Bibliography

Ailawadi, Kusum L., Paul W. Farris. 2013. How Companies Can Get Smart About Raising Prices. http://www.wsj.com/articles/SB10001424127887323734304578543202877975478. Accessed: 2016-01-18.

Alford, Bruce L, Abhijit Biswas. 2002. The effects of discount level, price consciousness and sale proneness on consumers' price perception and behavioral intention. *Journal of Business Research* **55**(9) 775–783.

Anderson, Chris K, John G Wilson. 2003. Wait or buy? the strategic consumer: Pricing and profit implications. *Journal of the Operational Research Society* **54**(3) 299–306.

Aviv, Yossi, Amit Pazgal. 2008. Optimal pricing of seasonal products in the presence of forward-looking consumers. *Manufacturing & Service Operations Management* **10**(3) 339–359.

Bagwell, Kyle, Michael H Riordan. 1991. High and declining prices signal product quality. *The American Economic Review* 224–239.

Baron, Opher, Ming Hu, Sami Najafi-Asadolahi, Qu Qian. 2015. Newsvendor selling to loss-averse consumers with stochastic reference points. *Manufacturing & Service Operations Management* .

Besbes, Omar, Ilan Lobel. 2015. Intertemporal price discrimination: Structure and computation of optimal policies. *Management Science* **61**(1) 92–110.

Biswas, Abhijit, Edward A Blair. 1991. Contextual effects of reference prices in retail advertisements. *The Journal of Marketing* 1–12.

Blattberg, Robert C, Richard Briesch, Edward J Fox. 1995. How promotions work. *Marketing science* **14**(3_supplement) G122–G132.

Bozdogan, Hamparsum. 1987. Model selection and akaike's information criterion (aic): The general theory and its analytical extensions. *Psychometrika* **52**(3) 345–370.

Buchanan, Lauranne, Carolyn J Simmons, Barbara A Bickart. 1999. Brand equity dilution: retailer display and context brand effects. *Journal of Marketing Research* 345–355.

Buhrmester, Michael, Tracy Kwang, Samuel D Gosling. 2011. Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science* **6**(1) 3–5.

Caves, Richard E, David P Greene. 1996. Brands' quality levels, prices, and advertising outlays: empirical evidence on signals and information costs. *International Journal of Industrial Organization* **14**(1) 29–52.

Chambers, Chester, Panos Kouvelis, John Semple. 2006. Quality-based competition, profitability, and variable costs. *Management Science* **52**(12) 1884–1895.

Chang, Tung-Zong, Albert R Wildt. 1994. Price, product information, and purchase intention: An empirical study. *Journal of the Academy of Marketing Science* **22**(1) 16–27.

Chen, Yiwei, Vivek F Farias. 2015. Robust dynamic pricing with strategic customers. *Proceedings of the Sixteenth ACM Conference on Economics and Computation*. ACM, 777–777.

Chevalier, Judith, Austan Goolsbee. 2009. Are durable goods consumers forward-looking? evidence from college textbooks. *The Quarterly Journal of Economics* **124**(4) 1853–1884.

Cho, Minho, Ming Fan, Yong-Pin Zhou. 2009. Strategic consumer response to dynamic pricing of perishable products. *Consumer-Driven Demand and Operations Management Models*. Springer, 435–458.

Choudhary, Vidyanand, Anindya Ghose, Tridas Mukhopadhyay, Uday Rajan. 2005. Personalized pricing and quality differentiation. *Management Science* **51**(7) 1120–1130.

Cohen, Maxime C, Ngai-Hang Z Leung, Kiran Panchamgam, Georgia Perakis, Anthony Smith. 2014. The impact of linear optimization on promotion planning. *Available at SSRN 2382251* .

Compeau, Larry D, Dhruv Grewal. 1998. Comparative price advertising: an integrative review. *Journal of Public Policy & Marketing* 257–273.

Darke, Peter R, Cindy MY Chung. 2005. Effects of pricing and promotion on consumer perceptions: it depends on how you frame it. *Journal of Retailing* **81**(1) 35–47.

Darke, Peter R, Darren W Dahl. 2003. Fairness and discounts: the subjective value of a bargain. *Journal of Consumer Psychology* **13**(3) 328–338.

Dodds, William B, Kent B Monroe, Dhruv Grewal. 1991. Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research* 307–319.

Elmaghraby, Wedad, Altan Gülcü, Pinar Keskinocak. 2008. Designing optimal preannounced markdowns in the presence of rational customers with multiunit demands. *Manufacturing & Service Operations Management* **10**(1) 126–148.

Erdem, Tülin, Michael P Keane. 1996. Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science* **15**(1) 1–20.

Gabor, Andre, Clive WJ Granger. 1966. Price as an indicator of quality: Report on an enquiry. *Economica* 43–70.

Gerstner, Eitan. 1985. Do higher prices signal higher quality? *Journal of Marketing Research* 209–215.

González, Eva M, Eduardo Esteva, Anne L Roggeveen, Dhruv Grewal. 2016. Amount off versus percentage offâĂŤwhen does it matter? *Journal of Business Research* **69**(3) 1022–1027.

Grewal, Dhruv, R Krishnan, Julie Baker, Norm Borin. 1998. The effect of store name, brand name and price discounts on consumers' evaluations and purchase intentions. *Journal of Retailing* **74**(3) 331–352.

Gumpert, Kiley, Siddharth Cavale. 2015. Holiday shopping season forecast: consumers fight for deals. `http://www.reuters.com/article/us-usa-retail-holidays-idUSKCN0RZ11Q20151005`. Accessed: 2016-01-08.

Gupta, Sunil, Lee G Cooper. 1992. The discounting of discounts and promotion thresholds. *Journal of Consumer Research* 401–411.

Hardesty, David M, William O Bearden. 2003. Consumer evaluations of different promotion types and price presentations: the moderating role of promotional benefit level. *Journal of Retailing* **79**(1) 17–25.

Harsha, Pavithra, Ngai-Hang Leung, Georgia Perakis. 2011. Markdown optimization for a fashion e-tailer: The impact of returning customers. *Working Paper* .

Heidhues, Paul, Botond Kőszegi. 2008. Competition and price variation when consumers are loss averse. *The American Economic Review* 1245–1268.

Hendel, Igal, Aviv Nevo. 2006. Measuring the implications of sales and consumer inventory behavior. *Econometrica* **74**(6) 1637–1673.

Ho, Teck H, Noah Lim, Colin F Camerer. 2006. Modeling the psychology of consumer and firm behavior with behavioral economics. *Journal of Marketing Research* **43**(3) 307–331.

Hoch, Stephen J, John Deighton. 1989. Managing what consumers learn from experience. *The Journal of Marketing* 1–20.

Hunt, Kenneth A, Susan M Keaveney. 1994. A process model of the effects of price promotions on brand image. *Psychology & Marketing* **11**(6) 511–532.

Jacobson, Robert, Carl Obermiller. 1990. The formation of expected future price: A reference price for forward-looking consumers. *Journal of Consumer Research* 420–432.

Janiszewski, Chris, Stijn MJ Van Osselaer. 2000. A connectionist model of brand–quality associations. *Journal of Marketing Research* **37**(3) 331–350.

Kalra, Ajay, Shibo Li. 2008. Signaling quality through specialization. *Marketing Science* **27**(2) 168–184.

Kardes, Frank R, Steven S Posavac, Maria L Cronley, Paul Herr. 2008. Consumer inference. *Handbook of Consumer Psychology* .

Kirmani, Amna, Peter Wright. 1989. Money talks: Perceived advertising expense and expected product quality. *Journal of Consumer Research* 344–353.

Knauth, Oswald. 1949. Considerations in the setting of retail prices. *The Journal of Marketing* 1–12.

Kőszegi, Botond, Matthew Rabin. 2006. A model of reference-dependent preferences. *The Quarterly Journal of Economics* 1133–1165.

Krishna, Aradhna, Imran S Currim, Robert Shoemaker. 1991. Consumer perceptions of promotional activity. *Journal of Marketing* **55** 4.

Levina, Tatsiana, Yuri Levin, Jeff McGill, Mikhail Nediak. 2009. Dynamic pricing with online learning and strategic consumers: an application of the aggregating algorithm. *Operations Research* **57**(2) 327–341.

Li, Jun, Nelson Granados, Serguei Netessine. 2014. Are consumers strategic? structural estimation from the air-travel industry. *Management Science* **60**(9) 2114–2137.

Lichtenstein, Donald R, Scot Burton. 1989. The relationship between perceived and objective price-quality. *Journal of Marketing Research* 429–443.

Lichtenstein, Donald R, Scot Burton, Eric J Karson. 1991. The effect of semantic cues on consumer perceptions of reference price ads. *Journal of Consumer Research* 380–391.

Luce, Mary Frances, John W. Payne, James R. Bettman. 1999. Emotional trade-off difficulty and choice. *Journal of Marketing Research* **36**(2) 143–159.

Mason, Winter, Siddharth Suri. 2012. Conducting behavioral research on amazonâĂŹs mechanical turk. *Behavior research methods* **44**(1) 1–23.

McConnell, J Douglas. 1968. The price-quality relationship in an experimental setting. *Journal of Marketing Research* 300–303.

McDougall, Gordon HG, Terrence Levesque. 2000. Customer satisfaction with services: putting perceived value into the equation. *Journal of Services Marketing* **14**(5) 392–410.

Monroe, Kent B. 1973. Buyers' subjective perceptions of price. *Journal of Marketing Research* 70–80.

Moorman, Christine. 2015. Cmo survey reports. Tech. rep., Duke University.

Nair, H. 2007. Intertemporal price discrimination with forward-looking consumers: Application to the us market for console video-games. *Quantitative Marketing and Economics* **5**(3) 239–292.

Narasimhan, Chakravarthi, Chuan He, Eric T Anderson, Lyle Brenner, Preyas Desai, Dmitri Kuksov, Paul Messinger, Sridhar Moorthy, Joseph Nunes, Yuval Rottenstreich, et al. 2005. Incorporating behavioral anomalies in strategic models. *Marketing Letters* **16**(3-4) 361–373.

Nasiry, Javad, Ioana Popescu. 2011. Dynamic pricing with loss-averse consumers and peak-end anchoring. *Operations research* **59**(6) 1361–1368.

Netessine, Serguei, Christopher S Tang. 2009. *Consumer-driven demand and operations management models: a systematic study of information-technology-enabled sales mechanisms*, vol. 131. Springer Science & Business Media.

Orth, Ulrich R, Pavel Krška. 2001. Quality signals in wine marketing: the role of exhibition awards. *The International Food and Agribusiness Management Review* **4**(4) 385–397.

Özer, Özalp, Robert Phillips. 2012. *The Oxford handbook of pricing management*. Oxford University Press.

Özer, Özalp, Yanchong Zheng. 2015. Markdown or everyday low price? the role of behavioral motives. *Management Science* .

Paolacci, Gabriele, Jesse Chandler, Panagiotis G Ipeirotis. 2010. Running experiments on amazon mechanical turk. *Judgment and Decision Making* **5**(5) 411–419.

Papatla, Purushottam, Lakshman Krishnamurthi. 1996. Measuring the dynamic effects of promotions on brand choice. *Journal of Marketing Research* 20–35.

Pashigian, B Peter. 1988. Demand uncertainty and sales: A study of fashion and markdown pricing. *The American Economic Review* 936–953.

Peterson, Robert A, Alain J Jolibert. 1976. A cross-national investigation of price and brand as determinants of perceived product quality. *Journal of Applied Psychology* **61**(4) 533.

Popescu, Ioana, Yaozhong Wu. 2007. Dynamic pricing strategies with reference effects. *Operations Research* **55**(3) 413–429.

Raghubir, Priya, Kim Corfman. 1999. When do price promotions affect pretrial brand evaluations? *Journal of Marketing Research* 211–222.

Rao, Akshay R, Kent B Monroe. 1989. The effect of price, brand name, and store name on buyers' perceptions of product quality: An integrative review. *Journal of Marketing Research* 351–357.

Rao, AR, KB Monroe. 1988. The moderating effect of prior knowledge on cue utilization in product evaluations. *Journal of Consumer Research* **15** 253–264.

Rao, AR, WA Sieben. 1992. The effect of prior knowledge on price acceptability and the type of information examined. *Journal of Consumer Research* **19**(2) 256–270.

Shapiro, Carl. 1983. Premiums for high quality products as returns to reputations. *The Quarterly Journal of Economics* 659–679.

Shell, Ellen Ruppel. 2009. *Cheap: The high cost of discount culture*. Penguin.

Shen, Zuo-Jun Max, Xuanming Su. 2007. Customer behavior modeling in revenue management and auctions: A review and new research opportunities. *Production and Operations Management* **16**(6) 713–728.

Snow, J, M Mann. 2013. Qualtrics survey software: handbook for research professionals.

Stafford, James E, Ben M Enis. 1969. The price-quality relationship: An extension. *Journal of Marketing Research* 456–458.

Stout, Hilary. 2013. For shoppers, next level of instant gratification. *New York Times* **8**.

Su, Xuanming. 2007. Intertemporal pricing with strategic customer behavior. *Management Science* **53**(5) 726–741.

Suk, Kwanho, Jiheon Lee, Donald R Lichtenstein. 2012. The influence of price presentation order on consumer choice. *Journal of Marketing Research* **49**(5) 708–717.

Sweeney, Jillian C, Geoffrey N Soutar. 2001. Consumer perceived value: The development of a multiple item scale. *Journal of Retailing* **77**(2) 203–220.

Talluri, Kalyan T, Garrett J van Ryzin. 2006. *The theory and practice of revenue management*, vol. 68. Springer Science & Business Media.

Taylor, Steven A, Thomas L Baker. 1994. An assessment of the relationship between service quality and customer satisfaction in the formation of consumers' purchase intentions. *Journal of Retailing* **70**(2) 163–178.

Tellis, Gerard J, Birger Wernerfelt. 1987. Competitive price and quality under asymmetric information. *Marketing Science* **6**(3) 240–253.

Tereyagoglu, Necati, Peter Fader, Senthil K Veeraraghavan. 2014. Multi-attribute loss aversion and reference dependence: Evidence from the performing arts industry. *Available at SSRN 2499265* .

Thomas, Manoj, Vicki G Morwitz. 2009. The ease-of-computation effect: The interplay of metacognitive experiences and naive theories in judgments of price differences. *Journal of Marketing Research* **46**(1) 81–91.

Völckner, Franziska, Julian Hofmann. 2007. The price-perceived quality relationship: A meta-analytic review and assessment of its determinants. *Marketing Letters* **18**(3) 181–196.

Waber, Rebecca L, Baba Shiv, Ziv Carmon, et al. 2008. Commercial features of placebo and therapeutic. *JAMA* **299**(9) 1016–1017.

Wheatley, John J, John SY Chiu. 1977. The effects of price, store image, and product and respondent characteristics on perceptions of quality. *Journal of Marketing Research* 181–186.

Zentes, Joachim, Dirk Morschett, Hanna Schramm-Klein. 2007. *Strategic retail management*. Springer.