OPTIMAL PRICING AND PROMOTION STRATEGIES IN IT-ENABLED RETAIL ENVIRONMENT

ZOU XIAO
(B. Comp. (Hons.), NUS)

A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF INFORMATION SYSTEMS

NATIONAL UNIVERSITY OF SINGAPORE

2015

DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

____

Zou Xiao

24 March 2015

ACKNOWLEDGEMENTS

First and foremost, I would like to express my most sincere gratitude to my supervisor Prof. Huang Ke-Wei for his guidance, inspiration and support throughout my PhD journey. I feel greatly humbled for the opportunities to work with him. Prof Huang's insightful comments and helpful advices have been always enlightened me to the completion of this work.

Second, my earnest appreciation goes to my dissertation committee members, Prof. Goh Khim Yong and Prof. Phan Tuan Quang for their valuable advices and guidance along the ways. I also thank all IS faculty members, especially IS economics group, for all the helpful comments and feedback during talks and seminars.

Thirds, to my fellow PhD friends, thank you very much for making my Ph.D. life a fruitful and memorable experience.

Last but not least, I wish to express my heartfelt thanks and love to my beloved parents and my wife, Guangnan, for her ever-lasting love, support and faith in me. To my daughter and son, thank you for bring me the love and joy when I am down. To them I dedicate this thesis.

TABLE OF CONTENTS

SUMMARY

The emergence of retail technologies and data analytics in recent times has drastically changed the retail industry landscape in terms of consumer behavior and firm pricing and promotion strategies. From consumers' perspective, consumers nowadays have access to channels such as mobile phones to get real-time price and promotion information about products and services. From retailers' perspective, most retailers have invested heavily in CRM systems and data analytics as the center of business activities. This thesis focuses on two recent retail technologies: Location-Based Service (LBS) and Customer Relationship Management (CRM) Systems; and studies their economic impact on pricing, promotion and competitive strategies. Study 1 presents a complete analytical study on optimal pricing and adoption strategy with LBS. The results show that in the optimal LBS strategy for LBS infomediary as a coupon delivery channel, retailers either adopt or reject LBS together, depending on the size of uninformed segments and reach of LBS. The location feature of LBS allows the retailers to price more aggressively in order to garner greater demand at the initial stage, which in turn limits the equilibrium profit in the subsequent pricing stages. We compare the results for both Internet and LBS infomediaries, and discuss the implications of our findings on retailers' pricing, promotion and technology adoption strategies for LBS. Study 2 presents an empirical approach to determine the optimal pricing and promotion strategies based on behavioral-based segmentation. The business value of CRM Systems depends on whether retailers target the right customers, and employ targeted pricing and promotion strategies. By analyzing the data on consumer profile and purchase history from the CRM Systems of a fashion retailer, we have developed a customer profitability model and segmentation strategy based on consumer demographics and behavioral-based characteristics using the finite-fixture model. The results can be used to assess the profit impact of pricing and promotion, and provide key implications on optimal segment targeting strategy for both research and practice.

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION AND OVERVIEW

1.1 Research Background

The ubiquitous of retail information technology (IT) has led to unprecedented change in the retail industry. The recent emergence of retail technology and data analytics has drastically changed the landscape of retail industry in terms of consumer behavior and firms' pricing, promotion and competitive strategies. From the consumer perspective, consumers can now make use of channels such as mobile phones to get real-time price and promotion information about products and services. This has reduced the information asymmetry and posed a significant challenge to retailers in terms of pricing strategies in different channels. Moreover, mobile devices and apps can serve as an additional marketing channel for retailers to implement price discrimination. As a result of their strategic learning and multiplicity of channels, consumers are now more sophisticated about their purchase behavior.

From the retailer perspective, most retailers nowadays have invested heavily in Customer Relationship Management (CRM) and data analytics as the center of business activities. Specifically, retailers regularly use CRM (e.g., loyalty program) to collect customer data on every possible aspect in order to know more about consumer preferences and demands. The CRM data are widely used to determine the nature and price of products and services to be offered to customers, and the channels to be used at any given point of time. This includes promotion planning, discounting, and posted pricing. At the same time, the strategic learning and stockpiling behaviors of consumers pose significant challenges to the retailers' profit maximization goals in terms of optimal pricing and promotion planning. As a result, the adoption of these retail technologies bring significant challenges on pricing strategies and raise new theoretical and empirical issues connected with existing research.

This thesis aims to investigate the optimal pricing and promotional strategies in the dynamic IT-enabled retail environment. Specifically, it presents two studies focusing on the economic impact of two recent retail technologies: Location-Based Service (LBS) and Customer Relationship Management (CRM). First, LBS is broadly defined as: *any application, service, or campaign that incorporates the use of geographic location of the user to deliver a service or a marketing message* (Mobile Marketing Association 2011). LBS is unique in utilizing the location information of users in real time; many novel LBS services therefore do not have a counterpart in the traditional e-commerce world. The consumer and advertiser expenditure on LBS is expected to approach 10 Billion USD by 2016 (Strategy Analytics 2011). An increasing number of large businesses, such as Starbucks, American Express, and Wal-Mart, are already leveraging the features of LBS actively to drive store traffic, increase brand awareness and interact with consumers.

On the other hand, CRM has been integrated into every step of the business process, right from handling product inquiry, marketing & advertising, sales, transaction, and service (Sun 2006). In this study, CRM is defined as the practice of analyzing and utilizing marketing databases and leveraging communication technologies to determine corporate practices and methods that will maximize the lifetime value of each individual customer (Reinartz and

Kumar 2006). Through CRM system adoption, firms potentially gain repeat business and, at the same time, obtain rich consumer data to aid their future CRM efforts. CRM nowadays spans various industries, including retail, travel, and financial sector. For example, Tesco is one of the successful retailers that extensively use a customer database and is frequently cited in textbooks as a successful benchmark for database marketing (Reinartz and Kumar 2006). It is critical to study how CRM-based marketing mix and price markdown affect the contribution of the consumer segments to sales volumes and profitability.

Despite the prevalence of loyalty programs and CRM system implementation, their effectiveness vis-à-vis profit is not well understood (Bolton et al. 2000). However, on an average, the companies with loyalty programs posted a 2.28 percent comp sales increase, while those without loyalty programs saw 4.26 percent gains in the U.S. retail market (McKinsey 2012). A recent survey (Forrester Research 2013) reveals that more than half of companies value their loyalty programs as strategic priorities, but only 35% of their members redeem awards. Since less than half of a company’s customers are enrolled, the bottom line is that only 16% of the customer base is motivated by loyalty rewards. Although CRM benefits customers in terms of savings and satisfaction, the sales and profit impact is unclear and effective analytics is critical to achieve the desired targets.

In today’s competitive fashion market, segmentation is a key to effective customer profitability management. Segmentation helps optimize investments in product development, channel management and marketing communications. This study therefore aims to investigate how customer information from CRM system can be used to identify the target customers and optimal markdown pricing strategies to achieve profit maximization. Specifically, it is looking at implementing behavioral-based segmentation based on CRM in order to select the most profitable customers and offer optimal markdown strategies. With their underlying behavioral profiles, the approach helps retailers to build effective targeted pricing and marketing strategies. With the declining cost of implementation and ubiquity of CRM system adoption, behavioral-based segmentation is the key in target pricing. Retailers thereby optimize the allocation of total marketing spend, launch tailored CRM activities and effectively increase their sales margins and revenues.

1.2 Overview of Studies

This thesis presents two studies, using different methodologies, to analyze the pricing and promotion strategies in the technology-enabled retail environment. The multiple methodologies complement each other and allow us to investigate a variety of research issues from different perspectives.

1.2.1 The First Study

Chapter 2 presents a study that uses analytical modeling to delineate optimal pricing and adoption strategy with LBS. We build a novel model that integrates two most popular pricing models in literature, viz. Hotelling pricing model for analyzing location differentiation and 'Model of Sales' for analyzing couponing strategy. We consider a game in which the retailers first decide whether to adopt LBS. The LBS technology allows the retailers to offer one additional discount price to consumers and the consumers, in turn, can use LBS to compare prices of participating retailers. As a result, LBS plays the role of a new coupon delivery channel and a price comparison engine in this model at the same time. In Stage 2, consumers decide on the mall to be visited first based on the expected retail price. On reaching the mall, a proportion of the consumers with LBS will receive additional discounted prices from participating retailers. Consumers then make final purchase decisions based on the lowest price offered to them by retailers.

This study focuses on two key features of LBS: a new coupon delivery channel and a new infomediary meant to compare prices and products. Although retailers have long been offering paper coupons for many years, mobile platforms provide allow retailers to offer new fun-based, personalized coupons to potential buyers at significantly lower costs. According to a market research report, 47% of mobile consumers want retailers to send coupons to their mobile devices when they are in or near the store (Loyalty360). Foursquare is a pioneering service, having more than 40 million users worldwide as of 2014. The users of Foursquare earn badges and coupons for visiting (via check-in) restaurants and local stores multiple times. Following the success of Foursquare, many entertaining and novel coupon apps have emerged recently. For example, CheckPoints presents users with a list of available products in the nearby participating retailers. The shoppers can use the phone’s camera to scan the barcodes on those participating products to earn prizes, while users don't have to buy anything (Washington Post 2011). CheckPoints' retail partners are banking on the fact that most users will end up buying the products being scanned. Similarly, ShopKick partnered with Target, Macy's, Simon malls and other leading retailers to provide indoor LBS couponing services. ShopKick has installed sensors in store ceilings to track users' activities in a store. Users can collect points simply by roaming around in the retail stores. As a result, the number of store walk-ins increased 60%, and customers with ShopKick buy twice as often as non-ShopKick users (USA TODAY 2012). According to AC Nielson (2013), the majority of smartphone (63%) and tablet (53%) owners search and scan their ways to savings in aisles. And the savings continue at the checkout lane, where smartphone shoppers are more likely to use their devices for mobile coupons (34%) and payments (23%).

As an infomediary, LBS have changed the way consumers gather price and product information. Nearly 40% of smartphone owners use their phones for in-store price comparisons, making it the top mobile shopping-related activity (MarketWatch 2012). During the holiday season in 2011, 19% of consumers used their phones to compare products and prices in stores. This success is a result of the fact that app developers brilliantly utilize various features to make the search and price comparison easier than their e-commerce counterparts. With a smartphone, users can compare prices by using the following input methods: type in a product name (as in old days), scan a barcode or QR code on products, speak product’s name to an app, take a picture of the product, or simply point the camera to the product with Augmented Reality apps that automatically display the product information on screen of devices. For example, an app named Price Check by Amazon provides almost all the aforementioned input methods for the purpose of price comparison. The Google Shopper app shows all the places where an item is available, both online and in nearby physical stores. The Consumer Reports' Mobile Shopper app provides not only price comparison, but also group's expert ratings, reviews and buying advice.

These two unique features of LBS motivated us to study how the adoption of LBS apps could affect retailers' pricing and profitability. On the one hand, LBS couponing apps are likely to attract more traffic to the retailers' stores. On the other hand, price comparison apps and LBS couponing may intensify the price wars among retailers in the same neighborhood, leading to lower profit margins. It is not obvious that increases in sales volumes can outweigh the decreases in profit margins. In other words, in a game theoretic model, it is intriguing to study the equilibrium retailers' LBS pricing strategy, LBS adoption strategy and associated equilibrium profits.

We analyze the model by considering all three possible cases for LBS adoptions separately. In each case, we solve the game backward and derive the equilibrium pricing for each retailer. We then derive the optimal LBS strategy based on their equilibrium profits in the three possible cases. There are some interesting results. Firstly, the equilibrium adoption strategy of LBS is that 'neither of the retailers join the LBS' or 'both retailers join LBS', depending on the size of uninformed segment and reach of LBS; while the equilibrium for internet infomediary is that only one retailer adopts infomediary. Essentially, the location feature of LBS is likely to intensify the price competition as retailers would be compelled to price more aggressively to compete for consumers, which would resultantly limit the profit in the subsequent pricing stage. This negative competition effect overwhelms the positive effect of price discrimination and potential additional demand resulting from LBS adoption.

1.2.2 The Second Study

Chapter 3 presents an empirical study on optimal markdown strategies founded on behavioral-based segmentation. The ubiquitous implementation of CRM system and data analytics has drastically changed the landscape of retail industry in terms of consumer behavior, firm pricing and promotion strategies. The business value of CRM system relies on whether retailers can target the right customers and employ targeted pricing and promotion strategies.

Study 2 thus aims to propose an empirical approach to determine the optimal pricing and promotion strategies founded on behavioral-based segmentation in the fashion goods industry. Specifically, we focus on markdown pricing, which is the most commonly used strategic tool for profit maximization in seasonal goods industries such as apparels, ticketing and airlines. A behavioral-based segmentation founded on CRM selects the most profitable customers and offers optimal markdown strategies accordingly. The behavioral-based segmentation captures consumer heterogeneities from two aspects. Firstly, retailers differentiate their pricing and promotion efforts based on customer differences in demography and history at an individual level. Secondly, retailers further differentiate their pricing and marketing strategies based on customer differences in response to markdown and promotions. As a result, Chapter 3 focuses on the following research questions:

1. What are the distinct consumer segments, in terms of markdown sensitivities and promotion responsiveness, in the context of seasonal goods?
2. What is the profitability impact of markdown pricing and promotions for different consumer segments?
3. What are the optimal markdown levels for each consumer segment, for profit maximization?
4. What is the optimal target markdown strategy, based on the derived profitability segmentation?

By analyzing the data on consumers' profile and their purchase history from CRM system of a fashion retail chain and using a finite-fixture model, we develop a customer profitability model and segmentation strategy founded on consumer demographics and behavioral-based characteristics. The finite mixture modeling approach has been widely applied and its performance has been well documented in marketing and economics literature. The finite mixture model (Wedel and Kamakura 2000) is a modeling technique that is used to simultaneously derive segments and segment-specific weights that relate an outcome or dependent variable (e.g., demand or profit) to a set of independent or explanatory variables (e.g., markdown and promotion). The results are used to assess the impact of pricing and promotion on profits, and these have key implications on the optimal segment targeting strategy for both, research and practice.

1.3 Positions and Contribution

This thesis mainly focuses on assessing the economic impact of retail technology on the retailer market in terms of pricing/promotion strategies and profitability. Theoretically, the profitability of retail technologies implementation depends on the retailer's ability to devise successful price discrimination strategies based on effective segmentation strategies. In this thesis, we examine two types of segmentation and corresponding price discrimination strategies. Firstly, consumers can be heterogeneous in terms of their informational differentiation on price information about products and distance to shopping areas, and this is the focus of the first study of the thesis. In this case, IT plays a key role as a promotion channel for coupons as well as an infomediary. Secondly, consumers can be segmented on the basis of their actual historical purchase behavior. Behavioral-based segmentation allows the retailers to offer differentiated pricing and marketing strategies based on consumer level metrics as well as differences in responses. The resulting IT-enabled targeting strategy is a key factor in CRM success.

As discussed in the literature review sections in Chapter 2 and 3, this thesis focuses on how the adoption of the two retail technologies affect the consumer segmentations and associated pricing and promotion strategies. This thesis adopts multiple methodologies in order to make comprehensive investigations of the problem from both theoretical and empirical perspectives.

Specifically, the analytical results in Study 1 provide several implications for research. Firstly, this study addresses how LBS essentially changes the consumer segmentations. On the one hand, LBS as an additional coupon delivery channel increases retailers' ability to engage in price discrimination and attract more store traffic. On the other hand, the infomediary feature of LBS introduces intensified price competition among retailers in a given neighborhood. The interaction of the two effects reveals a unique dynamic in terms of adoption strategies, compared to the prevailing internet infomediary. Secondly, the derived equilibrium profit and pricing depend on the level of information differentiation, travel cost parameters, and the reach of LBS. More importantly, the equilibrium adoption pattern depends on relationships between the size of uninformed segment and adoption rate. Thirdly, our analysis highlights the strategic importance of posted prices and location competition in considering shopping malls concepts.

The empirical results in Study 2: This study aims to contribute to existing research from three perspectives. Firstly, this study contributes to research on consumer heterogeneity in sales responses. In particular, we consider behavior-based variables as covariates for segmentation. Previous studies mainly used a behavioral-based approach via cluster analysis for the purpose of segmentation. However, this has been largely ignored when applying finite-mixture modeling. Moreover, previous research also shows that a demographic-based approach is not very effective in FMM-based segmentation (Allenby and Rossi 1998). Given the modeling advantage of FMM, our analysis demonstrates how behavioral-based characteristics and responses from CRM can be effectively used in FMM-based segmentation in literature. Secondly, this study focuses on markdown pricing at the segment level; this has been largely ignored in markdown pricing studies, especially in an empirical context. On the one hand, existing studies on target pricing are analytical studies, in which consumer segments are often exogenously and explicitly assumed (e.g., (Chen and Zhang 2009)). On the other hand, empirical studies have largely ignored consumer heterogeneity in the investigation of markdown pricing for fashion goods (e.g., (Heching et al. 2002)). Last but not least, from the methodological point of view, our modeling procedure provides an empirical approach to determine the consumer segmentation and optimal markdown simultaneously. Subsequently, the analytical approach and profitability model can be used to determine the optimal level of markdown for consumer segments, which has key implication for practice. This approach offers critical insights for retailers to devise target markdown and promotion strategies. Most literature in marketing focuses on the selection of promising target customers for promotional campaigns and much less on addressing what specific offers to direct to the target groups (Reutterer et al. 2006). This study fills this important gap by focusing on profitability analysis at a consumer segment level.

2 STUDY 1: OPTIMAL PRICING AND ADOPTION STRATEGY WITH LOCATION-BASED SERVICES

2.1 Introduction

Motivated by the explosive growth of location-based service and its two features, this chapter aims to study how the adoption of LBS apps may affect retailers' pricing strategies and profitability. At one hand, LBS couponing apps may attract more traffic to the retailers' stores. On the other hand, price comparison apps and LBS couponing may intensify the price wars among retailers in the same neighborhood, leading to lower profit margin. It is not obvious that the increases in sales volume can outweigh the decreases in profit margin. In other words, it is intriguing to study in a game theoretic model, what are the equilibrium retailers' LBS pricing strategy, LBS adoption strategy, and the associated equilibrium profits.

First, retailers have long been offering paper coupons for many years. Mobile platforms provide retailers new opportunities to offer potential buyers personalized coupons with fun to play at low costs. According to a market study, 47% of mobile consumers want retailers to send coupons to their devices when they are in or near the store (Loyalty360 2013). The pioneering, most successful vendor is Foursquare. Users of Foursquare can earn badges as well as coupons when visiting (via check-in) restaurants or other local stores several times. According to the official website, Foursquare has over 40 million users worldwide in 2013. Following Foursquare, many entertaining and novel coupon apps have emerged recently. For example, CheckPoints can present users with a list of available products in the nearby participating retailers. The shoppers use the phone's camera to scan the barcodes on those participating products to earn prizes while users don't have to buy anything (Washington Post 2011). CheckPoints' retail partners are banking on the fact that most users will end-up buying the product being scanned. Similarly, ShopKick partnered with Target, Macy's, Simon malls and other leading retailers to provide indoor LBS couponing. ShopKick installed sensors in store ceilings to track users' activities in a store. Users can collect points simply by roaming around in the retail stores. With ShopKick, the number of store walk-ins increased 60% and ShopKick users buy twice as often as non-ShopKick users (USA TODAY 2012). According to AC Nielson (2013), the majority of smartphone (63%) and tablet (53%) owners search and scan their ways to savings in aisles. And the savings continue at the checkout lane, where smartphone shoppers are more likely to use their devices for mobile coupons (34%) and for payment (23%).

As an infomediary, LBS have changed the way consumers gather price and product information (See appendix for an example of mobile app by *Yelp*). Nearly 40% of smartphone owners use their phones for in-store price comparisons, making it the top mobile shopping-related activity, according to MarketWatch (2012). During the holiday season in 2011, 19% of consumers used their phone to compare products or prices in store. This success results from the fact that app developers brilliantly utilize various features to make the search and price comparison easier than their e-commerce counterparts. With a smartphone, users can compare prices by the following input methods: type in a product name (as in old days), scan a barcode or QR code on products, speak a product's name to an app, taking a picture of the product, or simply point the camera to the product with Augmented Reality apps automatically displaying the product information on screen. For example, an app called Price Check by Amazon provides almost all aforementioned input methods for price comparison. Google Shopper app can show users all the places an item is available online and in nearby physical stores. Consumer Reports Mobile Shopper app provides users not only price comparison but also group's expert ratings, reviews and buying advice.

We build a novel model that integrates two most popular pricing models in the literature: Hotelling pricing model for analyzing location differentiation and "Model of Sales" for analyzing couponing strategy. We model a retailer market with two distant shopping malls, each of which has two retailers, at the two ends of a Hotelling line. On the Hotelling line, there are three groups of consumers, an assumption that is the same as in the "Model of Sales" by Varian (1980). Among three groups of consumers, two consumer segments are uninformed and only know about the price of one store. The remaining one segment is informed, smart shoppers who know the prices of both retailers. We consider a game in which the retailers first decide whether to adopt LBS. LBS allows the retailers to provide one additional discount price to consumer and the consumers can use LBS to compare prices of participating retailers. As a result, LBS in this model plays the role of a new coupon delivery channel and as a price comparison engine at the same time. In Stage 2, consumers will decide which mall to go first based on the expected retailers' price. Lastly, once consumers reach mall, a proportion of them with LBS will receive additional discounted prices from participating retailers. Consumers make final purchase decisions based on the lowest price offered to them.

We analyze the model by considering all three possible cases for LBS adoptions separately. In each case, we solve the game backwardly and derive the equilibrium pricing for each retailer. In particular, the third-stage store pricing game follows the existing results from existing literatures on price dispersion (Chen et al. 2002; Narasimhan 1988; Varian 1980) and treat LBS as a price referral infomediary. In Stage 2, we incorporate distance between the mall and posted prices into the model in order the capture the critical feature of LBS, the location. We then derive the optimal LBS strategy based on their equilibrium profits in the three possible cases. There are a few interesting results. First, the equilibrium adoption strategy of LBS is that “neither of retailers join the LBS” or “both retailers join LBS”, depending on the size of uninformed segment and reach of LBS; while the equilibrium for Internet infomediary is that only one retailer adopt infomediary. Essentially, the location feature of LBS is likely to intensify the price competition because retailers need to price more aggressively to compete for consumers, which in return, would limit the profit in the subsequent pricing stage. This negative competition effect overwhelms the positive effect due to price discrimination and potential additional demand resulting from adopting LBS.

This rest of the chapter is organized as follows: Section 2.2 reviews the related literatures. Section 2.3 discusses the details of model setup. Section 2.4 presents the analysis and discussions of results. Section 2.5 concludes this chapter.

2.2 Literature Review

2.2.1 Economics Literature on Price Dispersion

This study relates to the economics literature on price dispersion (Baye and Morgan 2001; Salop and Stiglitz 1977; Varian 1980). In these models, only a subset of consumers called informed consumers or smart shoppers are assumed to have access to a complete list of product prices and they can identify the product with the lowest price to buy. For instance, Varian (1980) shows that firms are more likely to charge either very high price or randomly offer different levels of discounts in a mixed strategy equilibrium. In this way, price dispersion is a price discrimination device between uninformed and informed consumers in the homogeneous goods market. The heterogeneity between these two types of consumers is also known as "informational differentiation". In other words, firms have the options of serving only the uninformed customers at a very high price or serving both informed and uninformed customers at a lower price. The seminal finding is that the equilibrium pricing strategy among competing retailers is a mixed pricing strategy equilibrium in which the retailers may randomly choose a discounted price to compete for the informed customers.

2.2.2 Marketing Literature on Sales and Promotion

By extending the solution concept of Varian (1980), several marketing studies have investigated various marketing issues such as consumer loyalty, sales/promotion strategy (Jing and Wen 2008; Narasimhan 1988), and referral infomediary (Chen et al. 2002). The key variables in these studies include the size of the loyal consumer segment (Jing and Wen 2008; Narasimhan 1988), magnitude of consumer loyalty (Jing and Wen 2008; Raju et al. 1990), as well as depth (Rao 1991) and frequency of the promotion (Narasimhan 1988; Rao 1991). In contrast to the economic literature, these marketing papers focus more on the modeling the demand-side properties as the explanations of price dispersion. Consistent with this literature in price infomediary, this study models promotional price competition by this setup because similar to Internet infomediary, one role of mobile LBS promotion is essentially a channel to let consumers become more informed about the price information from nearby retailers. One difference in this context is consumers have access to the in-store price since they are physically in the store and therefore, the mobile channel price must be lower than the in-store price. In contrast, retailers can set different prices in on different websites and the customers may not be aware that they are buying at a higher price at a price comparison site.

2.2.3 Information Systems Studies on Internet Referral Infomediary

Several studies in Information Systems have investigated the impact of Internet referral infomediary in the context of e-commerce and e-business. Bakos (1997) models the role of buyer search costs and examines the impact of electronic marketplaces on consumers' price discovery behavior. In the setting of supply-chain, Ghose et al. (2007) find that referral services play a critical role in enabling retailers to discriminate across consumers with different valuations. Moreover, Weber and Zheng (2007) analyze the firms' bidding strategies in intermediated search market, given consumers' equilibrium search behavior. Xu et al. (2010) study online search strategy. Bandyopadhyay et al. (2005) have derived mix-strategy pricing equilibrium for sellers in the context of online exchanges. Finally, Iyer and Pazgal (2003) have examined the impact of Internet

Shopping Agent on market competition. This model setup is in line with these studies. To the best of my knowledge, none of the existing studies has adopted this type of model to investigate the impacts of LBS price promotion.

This study can be considered as an extension of Chen et al. (2002), who analyze the effect of internet referral infomediary on retail markets. Specifically, we extend Chen et al. (2002) to model the mobile infomediary and couponing strategy in the last stage when consumers already arrive at the malls. We have extended their model by adding a 2nd stage Hotelling pricing game to investigate the impact of adopting LBS on the 3rd stage pricing and couponing strategies. More importantly, this study has compared the results of LBS infomediary with existing results of Internet infomediary. By this comparison, we can highlight the unique impacts LBS infomediary, relative to e-commerce infomediary.

2.3 Model Setup

2.3.1 Retailers

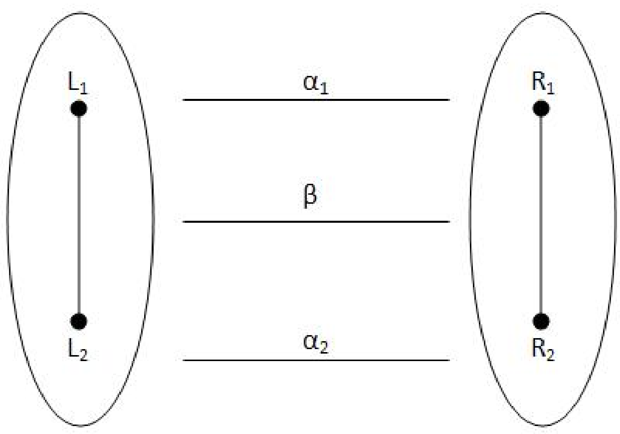


Figure 1 Retailers and Consumer in the Location Market

There are two shopping malls (or shopping districts) L and R at the end of a Hotelling line with the length normalized to 1 without loss of generality. In each mall, there are two retailers and the model can be generalized to a finite number of retailers as in the standard "model of sales" (Varian 1980). As shown in Figure 1, L_1 and L_2 are located in Mall L while R_1 and R_2 are located in Mall R. This shopping mall setup is the first main departure point from the existing literature in two ways. First, incorporating mall location allows us to model the distinctive feature of LBS; LBS provides product or price information only in one specific shopping district. Second, it allows us to incorporate the posted price strategy of retail chain stores, which has been under-explored in similar models. To model retail chain stores, we simply need to maximize the sum of profits of L_1 and R_1. For ease of exploration, we assume each store maximizes its store profit. An alternative way to see this setup is that L_1 and R_1 are individual retailer for homogenous goods or services. For example, both of them are fast-food restaurant but they are maximizing their own store profit. In this study, we assume L_1 and R_1 belong to Retail Chain 1 and L_2 and R_2 belongs to Retail 2. Retailers are risk neutral and they maximize expected profits. For ease of exposition, the variable cost of production and fixed cost are all assumed to be zero. The results can be generalized to a constant variable cost setup and fixed costs do not affect pricing at all, as in most existing pricing studies.

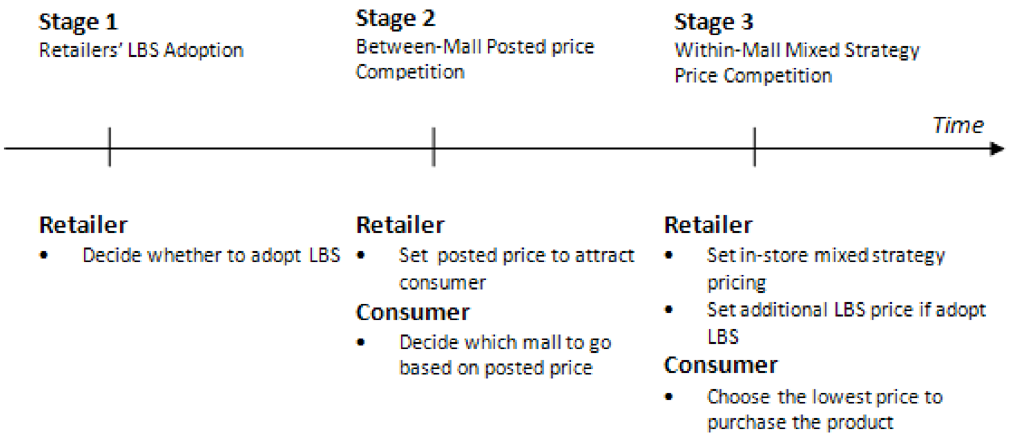


Figure 2 Sequence of the Game

2.3.2 The Sequence of the Game

The game in this study consists of three stages. In Stage 1, retail chains decide whether to adopt LBS. There are three possibilities: 1) Both retail chains adopt LBS; 2) Only one retail chain adopts LBS and 3) neither adopts LBS.

In Stage 2, all four retailers decide the original retail price. This price will be called posted price throughout this paper. Based on posted prices and the traveling cost in Hotelling model, consumers then decide which mall to visit. This posted price can be understood as "usual price" or "regular price" and is a common practice in the current retail industry. Due to the price dispersion, retailers seldom sell goods at this posted price, which serves as an upper bound on the actual level of price dispersion (Ghose and Yao 2011). Instead it is primarily used as a signal to attract customers to visit the shopping malls. Previous studies such as (Chen and Iyer 2002) has also explored the effect of similar posted price mechanism in the context of consumer addressability, in which firms simultaneously choose posted prices and then choose pricing strategies that are contingent on the previously chosen posted prices to their addressable consumer segments. In this way, a low posted price may attract more consumers to the mall, but it would limit the equilibrium price and profit level in subsequent stage. The consumer may conjecture that retailers may offer a lower price (than posted price) following a probability distribution (CDF) in store or via LBS.

In Stage 3, each retailer has to make one or two pricing decisions, depending on whether they adopted LBS or not in Stage 1. For retailers who do not adopt LBS, only one in-store promotional price will be offered to all consumer segments. For retailers with LBS, they can offer one additional LBS promotional price only to consumers who own smartphones equipped with the focal LBS app. In other words, retailer with LBS can set two prices, one in-store price and one LBS price, with price dispersion. The objective of retailers is to maximize expected profit by setting three prices (posted price, in-store promotional price and LBS promotional price) and one LBS adoption strategy. We assume both types of discounted prices are lower than the original price, which is consistent with the marketing practice. Consumers will choose the lowest price among the options offered to them to purchase the product. Please refer to Figure 2 for the timeline of this game. Details of the utility function of consumers will be discussed in the next section.

2.3.3 Consumers

The market consists of a unit mass of consumers on the Hotelling line. Consumers have identical valuation for visiting the mall and identical reservation price for buying the product. The identical valuation for mall is assumed to be v and without loss of generality, the reservation price is normalized to be 1 for simplicity. The unit traveling cost in Hotelling model is denoted by t.

Consistent with the price dispersion literature, consumers are assumed to be heterogeneous in terms of price information. Therefore, consumers are divided into three segments as in the literature. A proportion β of consumers have access to the price information of both retailers and will buy from the retailer that offers the lowest price. We call these smart shoppers "informed consumers" throughout this paper. There are two other groups of shoppers who only buy from one retailer respectively. We assume that α_i consumers are "uninformed consumers" who only buy from Retail Chain i $(i=1, 2)$. These consumers are interpreted as they do not know the focal product is also available at the other retailer, or these consumers do not have sufficient price or quality information about the other retailer. Hence, they are assumed to buy from their informed retailer but not the competing retailer. This setting implies $\alpha_1+\alpha_2+\beta=1$. To simplify the following analysis, we also assume $\alpha=\alpha_1=\alpha_2$ and focus on the symmetric setting. This symmetric setting approach has been widely adopted by many price dispersion studies (Chen et al. 2002). Asymmetric price dispersion models lead to qualitatively similar equilibrium with much more complicated algebra.

As explained in the sequence of game, consumers have two decisions to make. First, they decide which shopping mall to go. The choice of mall depends on two factors: first, the distance between the consumer and two shopping malls and second, the expected original prices of retailers within the same shopping mall. Informed and uninformed consumers will have different expected original prices. Since uninformed consumers only buy from one retailer (e.g., Retail Chain 1), they only compare the posted prices of L_1 and R_1. On the other hand, informed consumers would form their expectation by the average posted prices of two retailers because of symmetry and consumers has limited information about in-store price with dispersion.

Formally, Let the surplus for going to Mall *j* be U_j, and we have

$$U_j = \begin{cases} v - tx - p_{ij}^c & \text{for } \alpha \text{ segment} \\ v - tx - \dfrac{p_{1j}^c + p_{2j}^c}{2} & \text{for } \beta \text{ segment} \end{cases} \tag{0.1}$$

where $i = 1, 2$, $j = L, R$.

The reservation utility v for mall is assumed to be large enough so that every consumer will go to one of the two malls and the market is fully covered. As in all pricing models, consumers go to the shopping mall that gives them the higher surplus. Note that only informed consumers (β segment) make decision based on average prices and uninformed consumer (α_1 and α_2 segments) will not consider average posted prices.

Once they have reach the specific shopping mall, the second decision that consumers need to make is to choose a specific retailer to shop. At this stage, the uninformed consumers only buy from their informed stores. For example, L_1 consumers will only buy from the Store L_1; whereas the β consumers will buy from the store that offers the lower price. Let the utility of buying from Retailer i in Mall j be u_j, we have

$$u_j = \begin{cases} 1 - p_{ji} & \text{for } \alpha_i \text{ segment} \\ 1 - \min(p_{j1}, p_{j2}) & \text{for } \beta \text{ segment} \end{cases} \quad (0.2)$$

where $i = 1, 2, j = L, R$

In this setting, consumers make these two decisions separately. Specifically, the reservation utility for going to the mall v is different from the reservation utility for purchasing the final good, which is 1 in this setup. This assumption is consistent with the consumer behavior in practice; consumers typically go to mall for more than one purpose; $v>1$ because consumers also get benefits from window shopping, restaurants, and theaters in malls. When consumers adopted LBS apps, they will receive one more promotional price via the mobile channel, which is discussed in the next section.

2.3.4 The Impact of LBS

For the reach of LBS infomediary, we follow the setup by Chen et al. (2002). We assume that a fraction k $(0<k<1)$ of consumers who adopted LBS, which is exogenously given and is identical across all consumer segments. Consumers who use LBS will get additional price quotes from the retailers who adopt LBS. A consumer with price information obtained through both LBS and store will choose the lowest price and make purchase. In other words, the introduction of LBS as infomediary essentially create another channel for consumers to receive additional promotion quote and also learn the complete price information from all retailers who join the LBS infomediary. In this way, LBS significantly alter the consumer segmentation in the market with information differentiation, as shown in Figure 3 and 4 in the next section.

2.4 Analysis and Results

The model is solved by backward induction as in all other applied game theoretic models. We first analyze pricing equilibrium in the Stage 3, which is similar to either standard price dispersion games or the study by Chen et al. (2002), depending on the number of retailers who adopt LBS. Then we consider the Stage 2's posted pricing game, which is similar to a Hotelling pricing model. Finally, we derive the optimal LBS adoption strategy in Stage 1 by comparing the equilibrium profits derived in the three subgames (three combinations) of LBS adoption strategies.

2.4.1 Within-Mall Price Competition Game in Stage 3

In Stage 3, retailers can set in-store prices and LBS prices (if being adopted) to maximize profit, and consumers would choose one retailer to make the final purchase. In the analysis below, we discuss the equilibrium pricing and profit under three possible LBS adoption cases in the following subsections, respectively.

Case 1: Neither Retailer Adopt LBS

When neither retailers adopt LBS, this subgame is a standard price dispersion game in Varian (1980). The only difference is that the price cap in this price dispersion model is determined by the posted price set in Stage 2 of the model.

In Stage 3, the consumers have already arrived at the shopping malls. Since two malls are symmetric, we only need to solve the pricing game in mall L. Let us define D_L as the total number of consumers who go to Mall L. Among D_L, there are 3 types of consumers: two uninformed groups and one informed group of consumers. Denote those consumers in Mall *L* (originally from two uninformed segments α_1 and α_2) by D_{L1} and D_{L2}, respectively. Bear in mind that these uninformed consumers would only buy from retailers L_1 and L_2 respectively. By symmetry, we have $D_{L1} = D_{L2} = \alpha D_L$. Similarly, we denote the informed consumers in segment β in Mall L by βD_L, so $D_L = 2\alpha D_L + \beta D_L$. These informed consumers would buy from the retailer that offers the lower price. Retailer *i* in Mall *L* will choose price p_i to maximize the following profit function, given the price p_j from the competitor.

$$\pi_i(p_i, p_j) = \alpha D_L \times p_i + prob[p_j > p_i] \times \beta D_L \times p_i + prob[p_j = p_i]\frac{\beta D_L}{2} \cdot p_i . (0.3)$$

where $i \neq j$, $i, j = L_1, L_2$.

Following the standard solution procedure from the price dispersion literature (Narasimhan 1988; Varian 1980), we know that there is no pure-strategy Nash Equilibrium. In equilibrium all retailers adopt mixed-strategy pricing. In addition, let $F_i(p)$ be the cumulative distribution function (CDF) of price and π_i be the equilibrium profit for store i, we have the following lemma.

Lemma 1: *If neither retailer adopts LBS, given the demand in mall* D_L *and the price cap* p_i^c *, the profit and the equilibrium distribution function of price are*

$$\begin{aligned} &\pi_i = \alpha D_L \times p_i^c; \\ &F_i(p) = 1 - \frac{\alpha(p_i^c - p)}{\beta p}, \text{where} \frac{\alpha p_i^c}{\alpha + \beta} < p < p_i^c. \end{aligned} \tag{0.4}$$

This result is standard and can be found in Narasimhan (1988) and Varian (1980). One important property is that the retailer's equilibrium profit only depends on the size of uninformed segment αD_L and the posted price p_i^c . We will use these two properties as the building blocks to derive the solution for more complicated problems in Stage 1 and Stage 2.

Case 2: Both Retailers Adopt LBS

When both retailers adopt LBS, a proportion of the consumers (defined as the ratio *k*) can receive two additional LBS discounted prices on their smartphone. In total, now we have 6 types of consumers as illustrated in Figure 3. First, among the consumers who use LBS, we have a segment of $\beta \times k \times D_L$ informed consumers who know both in-store prices and they also receive two more LBS prices. They can make purchase at the lowest price among four available prices. As LBS prices are always lower than store price, the final purchase price of these consumers is essentially one of the two LBS prices. Second, segments of $2\alpha k D_L$ consumers will also receive two LBS prices from both stores and also one in-store price from their originally informed store. Since the LBS prices are lower than in-store prices, consumers in this segment become perfectly informed of price information of the two stores. They will also shop by the lower price among two available LBS prices. In other words, this $2\alpha k D_L$ consumer segment would become informed consumers because of LBS apps. Lastly, the remaining $(1-k)D_L$ consumers who do not adopt LBS will behave the same way as they were in Case 1. Figure 3 visualizes the impact of k on consumer segmentation.

Figure 3 Consumer Segmentation with LBS

As shown in Figure 3, kD_L (the shaded area) consumers receive discounted prices via LBS. This leads to Bertrand price competition within the kD_L segment. Therefore, the original price competition will be essentially for a smaller market with $(1-k)D_L$ consumers who do not use LBS. The solution is similar to those of Case 1. The difference only lies in the proportion of each consumer segment. As a result, we have the following lemma

Lemma 2*: If both retailers adopt LBS, given* D_L *and* p_i^c *, the equilibrium profit and the distribution function of price are*

$$\pi_i = (1-k)\alpha D_L \times p_i^c;$$
$$F_i(p) = 1 - \frac{\alpha(p_i^c - p)}{\beta p}, \text{where } \frac{\alpha p_i^c}{\alpha+\beta} < p < p_i^c. \tag{0.5}$$

Comparing Lemma 1 and 2, the profit of each store has decreased by $(1-k)$, which shows that the profit is strictly lower in this case when both retailers use LBS, due to the reduced information differentiation. Recall that we are analyzing two retailers who carry one homogeneous product. Originally in the price dispersion models, two retailers are differentiated by the product information available to consumers in the sense that some consumers only shop in one retailer because they do not know the same product is also available in a nearby competing retailer. With LBS apps, consumers become well-informed and the differentiation among retailers disappear. The aggravated price war ignited by LBS may cannibalize the existing profit, leading to an effectively shrunk market size to $(1-k)D_L$. Also bear in mind that although LBS leads to price war in Stage 3, it may attract more consumers to this mall in Stage 2, creating an intriguing trade-off in this model.

Case 3: Only One Retailer Adopt LBS

The most complicated yet unique subgame in the model is when only one retailer adopts LBS. Without loss of generality, let Retail Chain 1 be the store with LBS whereas Retail Chain 2 does not adopt LBS in this section. Again, we analyze the pricing problem in Mall L. Let the in-store price of Retail Chain 1 be p_{L1} and the LBS price be p_{L1}^{LBS}. Similar to the previous two cases, in the three consumer segments without LBS, the equilibrium pricing strategy is mixed-strategy pricing as usual in Case 1.

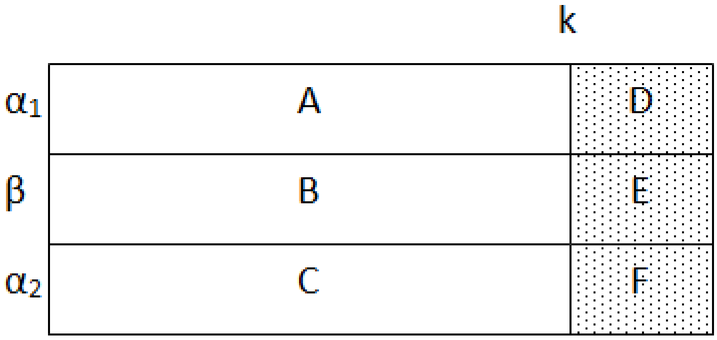


Figure 4 Consumer Segmentation (One Retailer Adopt)

Let D_{L1}, D_{L2} and D_L be the demand for Store L_1, L_2 and Mall L. By Chen et al. (2002), we can show that the prices offered via LBS channel will be lower than in-store prices (Chen et al., 2002, Proposition 1). As shown in Figure 4, for α_1 consumers who are informed of L_1, kD_{L1} (Area D) now will get lower price in LBS while kD_{L2} of segment α_2 (Area F) who are informed about L_2 will become the new informed consumers because they now know p_{L1}^{LBS} and p_{L2}. In this model, Chen et al. (2002) shows that Retailer 1 adopts mixed pricing strategies in both in-store (Area A,B,C) and LBS channels (Area D,E,F) whereas Retailer 2 adopts mixed pricing strategies in only one retail channel (Chen et al., 2002, Proposition 1 and 2). Following Chen et al. (2002) in equilibrium, the range of the price of retailer L_1 would be $p_{L1} \in (p_{L1}^m, p_{L1}^c)$ and the range of LBS price from retailer L_1 is $p_{L1}^{LBS} \in (p_{L1}^b, p_{L1}^m)$, where $p_{L1}^m = \dfrac{\alpha(1-\alpha)}{(1-\alpha)^2-(1-2\alpha)k} p_{L1}^c$ and $p_{L1}^b = (1-k)p_{L1}^m$. We follow their setup by assuming k<1-α so that $p_{L1}^{m} < p_{L1}^{c}$. For retailer L_2 (without LBS), the range of the price is $p_{L2}^{LBS} \in (p_{L2}^{b}, p_{L2}^{c})$, where $p_{L2}^{b} = \frac{\alpha(1-\alpha)}{(1-\alpha)^2 - (1-2\alpha)k} p_{L2}^{c}$. In other words, L_1 who uses LBS charges two different prices in two price intervals for the two channels respectively; whereas, L_2 who does not use LBS only charges regular store prices. Let $F_{L1}(p)$, $F_{L1}^{LBS}(p)$ and $F_{L2}(p)$ be the CDFs of prices. The equilibrium pricing and profit are summarized below.

Lemma 3*: If only one retailer adopt LBS, given* D_{L1}, D_{L2} D_L *and price cap* p_i^c *,the equilibrium price distribution functions and profit are*

$$\begin{aligned}
&\pi_{L1} = (1-k)\times D_{L1}\times p_{L1}^{c} + k\times D_L \times p_{L1}^{b} \\
&F_{L1}(p) = \frac{1-\alpha}{1-2\alpha}(1-\frac{p_{L1}^{m}}{p}), \quad where\ p_{L1}^{m} < p < p_{L1}^{c} \\
&F_{L1}^{LBS}(p) = \frac{1}{k}(1-\frac{p_{L1}^{b}}{p}), \qquad where\ p_{L1}^{b} < p < p_{L1}^{m}
\end{aligned} \tag{0.6}$$

The equilibrium pricing and profit are for Store L_2

$$\begin{aligned}
&\pi_{L2} = \left(D_L - D_{L1}\right) p_{L2}^{b}; \\
&F_{L2} = \begin{cases} 1-\dfrac{\alpha(p_{L2}^{c}-p)}{\beta p}, & for\ p_{L2}^{m} < p < p_{L2}^{c} \\ \dfrac{1}{1-\alpha}(1-\dfrac{p_{L2}^{b}}{p}), & for\ p_{L2}^{b} < p < p_{L2}^{m} \end{cases}
\end{aligned} \tag{0.7}$$

In the equilibrium mixed-strategy of pricing, there are two intervals of randomized pricing of each retailer. For Retailer 1, in-store price is randomized at a higher range to target at the consumers who do not have LBS whereas the LBS price is randomized at a lower range to target the consumers with LBS.

Retailer 2 will optimally react by offering one randomized price accordingly. The profit function in Lemma 3 reveals simple yet intuitive insights on profitability. Specifically, for π_{L1}, the first term represents the profit from regular store channel. When the store price is charged at p_{L1}^{c}, the demand that Retailer 1 get will be Area A with the size *(1-k)* $\times D_{L1}$. Similarly, the second term represents the profit from the LBS channel, i.e. Retailer 1 can get all demand from LBS channel (Area D, E & F) by charge the lowest possible price p_{L1}^{b}. On the other hand, Retailer 2 can get all demand except for Retailer 1's uninformed segment (Area A) by charging the lowest price in the price range.

From Retailer 1's perspective, the trade-off of offering extra discounts via LBS includes the following effects. First, the LBS channel allows Retailer 1 to poach the other retailer's uninformed consumer (Area F in Figure 4, which cannot be reached without LBS). Similar effect has been discussed in the paper by Chen et al. (2002). In other words, LBS can serve as a targeted advertising channel to poach the competitor's "uninformed" customers. The second (negative) effect is that the lowered LBS price may cannibalize the profit from Retailer 1's "loyal" customers in Area D in Figure 3. The last effect is that the LBS price may intensify the price war between two retailers. In equilibrium, Retailer 2 may react by more aggressive pricing because consumers are better informed in the LBS market.

2.4.2 Between-Mall Pricing Game in Stage 2

Let us consider the effect of posted prices and shopping mall locations. In Stage 2, both retailers announce the posted price through another channel or media (e.g. Newspaper, Catalog, Website etc.). The posted prices are common knowledge to all consumers. The introduction of posted price has two strategic effects. First, consumers decide which mall to go based on the posted prices. Second, posted price is also the price cap for pricing dispersion game in Stage 3. The first one affects retailers' profit positively as it increases the demand whereas the second one adversely affects retailers' profit because price cap inhibits retailers' flexibility in offering discounts in Stage 3. The objective of retailers is to set an intermediate, optimal posted price to maximize the store profits in Stage 2. For instance, a low posted price may attract more consumers to the mall, but it would limit the equilibrium price and profit level in Stage 3. The consumer may conjecture that retailers may offer a lower price (than posted price) following a probability distribution (e.g. CDF in Lemma 1, 2 & 3) in store or via LBS. Once the consumer enters the shopping mall in Stage 3, the consumer can know the actual prices offered, including in-store promotion price and LBS promotion price (for LBS users).

Again we analyze Mall L because of the symmetric setting. Based on the surplus for going to one specific mall defined in eq. (1), we can derive the demand function of Mall *L* in the three consumers segments. Specifically, denote $D_{L1}, D_{L2}, D_{L\beta}$ as the sizes of uninformed consumers for α_1, α_2 segments and β informed consumer, respectively. Similar to the demand function in standard Hotelling models, it follows that

$$
\begin{aligned}
&D_{L1}=\frac{\alpha}{2}+\frac{p_{R1}^{c}-p_{L1}^{c}}{2t} && \text{in } \alpha_1 \text{ segment}\\
&D_{L2}=\frac{\alpha}{2}+\frac{p_{R2}^{c}-p_{L2}^{c}}{2t} && \text{in } \alpha_2 \text{ segment}\\
&D_{L\beta}=\frac{\beta}{2}+\frac{p_{R1}^{c}-p_{L1}^{c}+p_{R2}^{c}-p_{L2}^{c}}{4t} && \text{in } \beta \text{ segment}\\
&D_{L}=D_{L1}+D_{L2}+D_{L\beta}=\frac{1}{2}+\frac{3\left(p_{R1}^{c}-p_{L1}^{c}+p_{R2}^{c}-p_{L2}^{c}\right)}{4t}
\end{aligned}
\tag{0.8}
$$

Similar to Stage 3's subgames, we will examine three possible cases given the LBS adoption strategy in the first stage.

Case 1: Neither Retailer Adopt LBS

Based on Lemma 1, we have derived the profit function which only depends on the total demand D_L and price cap.

$$
\begin{aligned}
&\pi_i=\alpha D_L \times p_i^c,\\
&\pi_j=\alpha\left(1-D_L\right)p_j^c.
\end{aligned}
$$

where $i=L_1, L_2$ *and* $j=R_1, R_2$.

The retailers' maximization problem is then specified as

$$\max_{p_i^c} \pi_i$$

By substituting Lemma 1 into above profit functions and take first-order condition (FOC), we have a system of equation for four retailers. As all retailers are symmetric we summarize the result in the following proposition.

Proposition 1*: If neither retailer adopts LBS, the equilibrium posted price and profit are*

$$\begin{aligned} p_i^c &= \frac{2}{3}t, \\ \pi_i &= \frac{t\alpha}{3}, \end{aligned} \tag{0.9}$$

where $i=L_1, L_2, R_1, R_2$.

As shown in the results above, the equilibrium posted price and profit depend on the size of uninformed segment α and the location parameter t. It is straightforward that the critical feature of LBS, the location, plays a significant role in determining the equilibrium price and profit. As t increases the profit of retailer increases, which means that the more the shopping malls are differentiated or distant, the more profit each retailers will get. This is consistent with the conventional wisdom of models on location competition. Meanwhile, in order to make the posted price mechanism behaves in order, posted price must be less or equals to 1, which is the reservation prices of consumers. In other words, t needs to be relatively small. This finding explains why many LBS as infomediary mobile applications are only widely used in urban areas where shopping malls are not distant enough.

Case 2: Both Retailers Adopt LBS

In this case, we still assume the proportion of consumers who adopted LBS as *k*. By the similar procedure in Case 1, essentially we solve Case 1 with a smaller market size with (1-k) of the size. The equilibrium posted prices and profit are reported in the following proposition.

Proposition 2*: If both retailers adopt LBS, the equilibrium posted price and profit are*

$$\begin{aligned} p_i^c &= \frac{2}{3}t, \\ \pi_i &= \frac{t\alpha}{3}(1-k), \end{aligned} \tag{0.10}$$

where $i=L_1, L_2, R_1, R_2$.

Basically the posted prices are not affected and the profit becomes strictly lower than that in Case 1. Intuitively, the introduction of LBS would decrease the profit because it intensifies price competition by reducing the differentiation between two retailers.

Only One Retailer Adopt LBS

When only one retailer adopted the LBS, the solution becomes fairly complicated because of the asymmetric setting. Without loss of generality, assume only L_1 adopted LBS and L_2 did not. Similar to Cases 1 and 2, substituting eq. (6) and (7) into the profit functions eq. (8), we then solve the first-order-conditions for equilibrium pricing and profit. Results are shown as follows.

Proposition 3*: If only Retailer 1 adopts LBS, the equilibrium posted price and profit are as follow.*

$$p_i^c = \frac{2t\alpha((1-\alpha)^2 + k\alpha)}{k(3\alpha-1)(2-\alpha)+2(1-\alpha)^2},$$
$$\pi_i = \frac{t\alpha^2(1-k)(\left(1-\alpha\right)^2 + k\alpha)^2}{(k(3\alpha-1)(2-\alpha)+2(1-\alpha)^2)((1-\alpha)^2-(1-2\alpha)k)}, \tag{0.11}$$

where $i=L_1, L_2$.

For Retailer 2 who does not adopt LBS,

$$p_j^c = \frac{2}{3}t(1\text{-}\alpha),$$
$$\pi_j = \frac{\alpha t\left(1-\alpha\right)^3(1-k)}{3\left((1-\alpha)^2-(1-2\alpha)k\right)}, \tag{0.12}$$

where $j=L_2, R_2$.

2.4.3 LBS Adoption Game in the First Stage

Equilibrium LBS Adoption Strategy

By comparing equilibrium profits derived previously, we can have the following proposition for the LBS adoption strategy. Detailed proof is discussed in the Appendix.

Proposition 4*: Among all three possible adoption scenarios, the equilibrium LBS adoption strategy is summarized as follow:*

1. *If $\alpha \geq \frac{1}{3}$, there are two pure strategy Nash equilibria for "Both retailers adopt" and "Neither retailers adopt", and a mixed strategy between the two.*
2. *If $\alpha < \frac{1}{3}$, the equilibrium depends on the value of k,*
    a. *If $k \leq \frac{\alpha(1-\alpha)^2}{1-2\alpha}$, there are two pure strategy Nash equilibria for "Both retailers adopt" and "Neither retailers adopt", and a mixed strategy between the two.*
    b. *If $k > \frac{\alpha(1-\alpha)^2}{1-2\alpha}$, there is one pure strategy Nash equilibrium is "Neither retailers adopt".*

Overall, the above proposition reveals that the optimal LBS adoption behaves like a classic coordination problem, in which both retailers either join or do not join together. The specific optimal LBS strategy depends on the value of α and k. Intuitively, increasing α has a positive impact on retailer's profit because of increase in brand differentiation, because it implies more consumers are uninformed and only visits one retailer; while increasing k negatively affects retailers' profit because it implies that more consumers become well-informed by adopting LBS and the LBS price is lower than the in-store prices. As shown in Proposition 4-1, when α is large, the potential additional demand (depends on α) that can be poached from competitor's original uninformed segment could be relatively large, which is the main benefit of adopting LBS. Therefore "Both retailers adopt" could be a viable equilibrium strategy for both retailers, even it is suboptimal compared to the case without LBS because of competition effect. Moreover, when α is relatively small, as long as k is relatively small (*Proposition 4-2a*), the positive benefit from adopting LBS could offset the negative effect due to intensified price competition from the LBS channel. Thus the two retailers could still join LBS together. However, when α is small and k is large (*Proposition 4-2b*), the unique pure LBS strategy is "Neither retailers adopt" because the negative effect of LBS is larger than the benefit from LBS adoption.

By far, we have always assumed the reach of LBS *k* is the same for uninformed and informed consumers for simplicity. In practice, we would expect the informed consumers have a much higher LBS adoption rate than the uninformed consumers. Now let the reach of LBS for uninformed consumer segment be *k* and the reach for informed consumer segments be *k'*, where *k'*>*k*. A graphical illustration of such case is that a small proportion of Area B is not in Area E in Figure 4. We are interested in how a different k' may affect the results of the model.

First, it is straightforward to see that the profit of Case 1 (without LBS) remains unchanged (Proposition 1). Second, the profit for Case 2 (both LBS) remains unchanged too, because the profit is based on the size of uninformed consumers who are not using LBS, the proportion of which is still k in this setting. Lastly, for the most complicated Case 3, consider the profit in Proposition 6, generally we can show that the profit for Retailer 1 is an increasing function of k, whereas Retailer 2's profit is decreasing in k[1]. Intuitively, when *k'* increases, the value of LBS increases and Retailer 1 is better off with higher profit by extracting more demand and profit from LBS channel; whereas Retailer 2 is worse off in return. If we consider the change in the pay-off matrix that is illustrated in the proof of Proposition 7 in Appendix, with *k'*, Profit A and B remain unchanged. C increases while D decrease. Ultimately, as the *k'* increases, we would have C>B and A>D, and the equilibrium adoption would be (A, A), i.e. "both retailers adopt".

Generally, we show that consideration of two different values of k for informed and uninformed consumers do not significantly affect the results of

[1] To see this, it is trivial to verified that $d\pi_i \,/\, dk > 0$ and $d\pi_j \,/\, dk < 0$ in Proposition 3, given the condition that $k < 1 - \alpha$ and $k' < 1 - \alpha$.

equilibrium adoption, in which coordination of adoption could be optimal for both retailers. Essentially, increasing k' transfers part of informed consumers from regular store channel (Area B) to LBS channel (Area E) in Figure 4, which increases the value of LBS channel and creates a different dynamic of adoption pattern.

Traditional Infomediary vs. LBS Infomediary

Consider a special case of our model to benchmark our results and highlight the unique adoption pattern. If we omit the second stage of the game, in which retailers decide posted prices to maximize their profits, we are able to re-examine the equilibrium profits and LBS strategy of the Internet Infomediary by omitting the location of shopping malls. In this study, we call this Internet infomediary the "Traditional Infomediary" because it has been prevailing with the growth of e-commerce in the past two decades. This Internet infomediary has brought benefit to consumers by reducing search cost, because consumers can use this service to research price information from retailers. Specifically, we extend Chen et al. (2002) by incorporating the "shopping mall" concept and the location dimension to capture the distinctive feature of LBS. In this section, we solve this special case of traditional infomediary in our setting and compare the results with LBS infomediary.

In this section, there are no posted prices setting stage. In other words, consumers would only consider travel cost when deciding which mall to visit.

As a result, there are half of the consumers in each segment that visits one mall. In this setting, exactly $\alpha + \frac{\beta}{2}$ consumers visit each mall. In one particular mall, there are $\frac{\alpha}{2}$ segment of uninformed consumers for L_1 and L_2, respectively and another $\frac{\beta}{2}$ segment of informed consumers who shop at both retailers. Hence, we have $D_{L1} = D_{L2} = \frac{\alpha}{2}, D_{L\beta} = \frac{\beta}{2}$ and $D_L = \frac{1}{2}$. Note that all these values are now exogenous since we omit posted price competition. Further, the price cap for store prices will be the reservation price, which is 1 in the model. Based on above lemmas and propositions, we can solve the equilibrium pricing and profit.

The result is generally consistent with Chen et al. (2002). Comparing the profits in three adoption cases, we find that the case when only one retailer adopts Internet Infomediary yields the highest profit for both retailers. By similar approach, we can easily verify that the equilibrium adoption pattern is that only one retailer will join the Internet Infomediary.

We can then compare the equilibrium profit of the two types of infomediary for all three adoption cases in the following table. First, it is straightforward to observe that "Neither adopt" always dominates "Both adopt" in both types of Infomediary. More importantly, the dynamic of the LBS adoption decision has also changed dramatically. In particular, "only one retailer adopts LBS" is the optimal LBS adoption strategy for Internet infomediary, while it is not the case for LBS infomediary and we observe a clear coordination game between retailers' adoption and an asymmetric adoption case is never optimal. The reason is that in the setting of Internet Infomediary, the retailer without infomediary (Retailer 2) gain higher profit than they may obtain to join the infomediary in the case of asymmetric adoption. In the LBS adoption game, the retailer without LBS may end up with very low profit. As a consequence, that retailer may also adopt LBS because of the competition from Retailer 1, even both retailers end up with lower profits than both of them do not adopt LBS.

Table 1 Comparison of Internet and LBS Infomediary

Case	Internet Infomediary	LBS Infomediary
Neither LBS	$\pi_i = \frac{\alpha}{2}$	$\pi_i = \frac{t\alpha}{3}$
Both LBS	$\pi_i = (1-k)\frac{\alpha}{2}$	$\pi_i = \frac{t\alpha}{3}(1-k)$
Only 1 LBS	$\pi_1 = (1-k)\frac{\alpha}{2}\frac{(1-\alpha)^2 + k\alpha}{(1-\alpha)^2 - (1-2\alpha)k}$ $\pi_{L2} = (1-k)\frac{\alpha}{2}\frac{(1-\alpha)^2}{(1-\alpha)^2 - (1-2\alpha)k}$	$\pi_1 = \frac{t\alpha^2(1-k)((1-\alpha)^2 + k\alpha)^2}{(k(3\alpha-1)(2-\alpha) + 2(1-\alpha)^2)((1-\alpha)^2 - (1-2\alpha)k)}$ $\pi_2 = \frac{\alpha t(1-\alpha)^3(1-k)}{3((1-\alpha)^2 - (1-2\alpha)k)}$

2.5 Discussion and Conclusion

In this study, we present a model on location-based service by synthesizing the price dispersion model with Hotelling location model and investigate the impact of LBS on retailers' pricing, profits and LBS adoption strategy. Specifically, we solve the game using backward induction in three adoption cases and derive the equilibrium profit and pricing accordingly. We analyze the equilibrium LBS adoption strategy by comparing profits in all adoption cases. Our results are used to compare against the benchmarking case, Internet infomediary, from the literature. The results show that the optimal adoption strategy in Internet infomediary is asymmetric. I.e. Only one retailer would adopt LBS. In contrast, in the LBS adoption game, the equilibrium is similar to that of a coordination game.

2.5.1 Implication for Research and Practice

Our analysis provides several implications for research. First, this study addresses how LBS essentially changes the consumer segmentations. On one hand, LBS as an additional coupon delivery channel increases retailers' ability to engage price discrimination and attract more store traffic. On the other hand, the infomediary feature of LBS introduces intensified price competition among retailers in the same neighborhood. The interaction of the two effects reveals unique dynamic in terms of adoption strategies, compared to the prevailing Internet infomediary. Second, the derived equilibrium profit and pricing depend on the level of information differentiation, travel cost parameter, and the reach of the LBS. More importantly, the equilibrium adoption pattern depends on relationships between the size of uninformed segment and adoption rate. Third, our analysis highlights the strategic importance of posted prices and location competition when considering shopping malls concepts.

The analytical results provide several implications for retailers in terms of pricing/promotion and LBS adoptions strategies. First, our results can help the retailers to design optimal promotional pricing strategies when LBS is adopted by herself and/or the competitor, especially within the same shopping region. The retailer could make use of the model to understand the key strategic impact of pricing variables for pricing decisions. For example, retailers should alleviate the posted price competition by setting a higher posted price. A low posted price may not increase overall profits because of local competition from the other retailer in the same mall. Second, our analysis provides key implications on LBS adoption strategy for retailers, based on the current competitive environment on store's brand awareness and the adoption rate of LBS. For example, a prevalent adoption of LBS is only optimal when there are a small proportion of informed shoppers who know both retailers' prices or the reach of LBS is very small. A small LBS adoption could happen in the early stage of adoption lifecycle. In practice, we do see that the LBS apps could be more popular and widely adopted by fashion retailers or restaurant, in which consumers are more locked-in to each brand due to strong consumer tastes/loyalty. Last but not least, because of distinct optimal adoption strategies in LBS (compared to Internet), retailers should not apply the conventional wisdom to follow the competitors' adoption strategy of new technologies, such as LBS. Instead, the retailers could assess the pay-off of different adoption scenarios based on market conditions described above. Under certain conditions, retailers should collude not to adopt LBS to gain higher profit, because LBS triggers the price war. Obviously, consumers gain the most from LBS because they have one more channel to receive discounted prices and they also have one new infomediary to compare prices from more retailers.

2.5.2 Limitation and Future Research

Our analysis has made a few assumptions that can be generalized in future works. First, we assume the reach of LBS in this model is exogenous, which could be relaxed to reflect the real business scenarios. In real world for many other applications with the feature of two-sided advertising platform, the adoption of this new platform by retailers should be endogenized. Although we provide simple intuition when the reach of LBS is not identical across segments, researchers could rigorously model the reach of infomediary as an endogenous variable in consumers' utility specification to generate more insights. Second, we have omitted the possible coordination strategy between retailer chains and retailers for ease of exploration. Particularly, this model considers profit maximization decision of each individual stores but not the retail chain for model tractability. It may be interesting to investigate an asymmetric setting in which one retail chain competes with two individual retailers. By this setting, we could analyze whether retailers chain may gain more than individual store by adopting LBS. Lastly, this study can be extended by considering vertically differentiated malls. It could be interesting to examine the retailers located in high-end or ordinary malls have stronger incentives to adopt LBS technologies.

3 STUDY 2: OPTIMAL MARKDOWN STRATEGY BASED ON BEHAVIORIAL-BASED SEGMENTATION: A FINITE-MIXTURE APPROACH

3.1 Introduction

With the ubiquitous implementation of customer relationship management systems, retailers have been able to collect a lot of information at the customer level, which include detailed customer purchase history, customer demographic and even customer attitudes via surveys. The ubiquity of retail data at the different levels and the emergence of retail analytics have created tremendous opportunities for both retail practitioners and researchers.

From the perspective of practitioners, even though the adoption of CRM system and loyalty program is prevalent due to the declining cost of implementation, however, the value and effectiveness of their implementation are debatable in the literature. A recent survey reveals that more than half of companies value their loyalty programs as strategic priorities, but only 35% of their members redeem awards, and only 16% are motivated by loyalty rewards (Forrester Research 2013). Dowling (2002) suggests that loyalty programs do not necessarily foster loyalty, they are not cost effective, and the proliferation of loyal programs is “hype” or a “me-too” scheme. Conversely, some recent studies show that loyalty programs have a positive impact on consumers’ re-patronage decisions and their share of wallet (Lewis 2004; Verhoef 2003). In fact, even with the ubiquity of CRM system implementation, many retailers do not collect the right data, analyze the data appropriately, or initiate the optimal marketing actions to achieve the best business objectives, which possibly have led to failure of CRM system implementations. As a result, retailers consistently struggle with building sustainable and profitable customer relationships. The business value of CRM system is usually based on the fact that whether retailers can target the right customers and employ targeted pricing and promotion strategies for profit maximization.

The empirical context of this study is the fashion apparel market, in which markdown pricing is the most commonly used strategic tool for profit maximization. Generally, in seasonal goods industries, such as fashion apparel, holiday merchandize and tickets of events, the unique demand characteristic, such as non-replenished and seasonality, play significant roles. The markdown pricing is a prevalent practice in fashion industry due to two reasons: Firstly, the growing competition in the industry makes pricing a major weapon for competition, especially during shopping seasons such as summer holiday and Christmas period. Secondly, the fast changing fashion trends require retailers to replenish the inventory after a season. As a result, markdown pricing has been used as a strategic tool for profit maximization—via price discrimination and targeting—and also for inventory control near the end of the season and product lifecycle.

In the environment of today’s competitive fashion market, segmentation becomes the key to effective customer profitability management. Segmentation refers to a strategic process of sub-dividing the consumers into relevant groups that share similar characteristics and are significantly different from other groups (Kotler and Keller 2011). Segmentation helps optimize investments in product development, channel management and marketing communications. Therefore, this study aims to investigate how customer-level information from CRM system can be used to understand who are the right customers to target and what are the optimal markdown pricing strategies for profit maximization. Identifying segments in a consumer population and determining their sensitivity to various pricing and promotion variables have been one of the most important research issues in the marketing literature due to their impact and the associated profit implication (Wedel and Kamakura 2000). Moreover, the determination of optimal marketing decisions must account for the substantial uncertainty that is a part of individual-level parameters (Allenby and Rossi 1998).

This study, using behavioral-based segmentation, captures consumer heterogeneities from two aspects. Firstly, retailers can differentiate their pricing and promotion efforts, based on customer demographics and history at individual level. Secondly, retailers can further differentiate their pricing and marketing strategies based on differences in customer response, which has been considered a key factor for CRM success.

We propose an empirical approach to perform behavioral-based segmentation based on CRM, which upon implementation can select most profitable customers and offer optimal markdown strategies accordingly. The approach helps retailers, with their underlying behavioral profiles, to build effective targeted pricing and marketing strategies. With the declining cost of implementation and ubiquity of CRM, behavioral-based segmentation is the key in target pricing. In this way, retailers optimize the allocation of the total marketing spend, launch tailored CRM activities and effectively increase their sales margins and revenue.

Various model specifications and methodological approaches have been proposed to delineate the underlying customer segments in a given market. Finite mixture modeling approach has been widely applied and its performance has been well documented in marketing and economics literature. Finite mixture model (Wedel and Kamakura 2000) refers to a modeling technique used to simultaneously derive segments and segment-specific weights that relate an outcome or dependent variable (e.g., product recommendation or rating) to a set of independent or explanatory variables (e.g., price of a product and product quality), and derive a unique regression model for each of the segments. The basic rationale of the finite mixture model is as follow: There are fixed and finite numbers of homogenous segments in a market or population. An individual belongs to each segment with some probability, which is assumed to be a priori invariant across the subjects. Being conditional upon the membership in a segment, the probability of an individual's response is pre-specified with varying parameter estimates across the segments. By maximizing the unconditional likelihood of the entire sample, the estimates of membership probability and the associated parameter estimates can be obtained simultaneously. Each subject then can be assigned to a segment based on the updated posterior segmentation probability.

Earlier studies on sales responses for markdown pricing and promotion mainly examine the effect of promotion at a brand level (Raju 2001). For example, how sales-promotions drive marketing outcomes such as sale-volume (demand), store visit, consumer share-of-wallet or brand choice. This study focuses on profit, which is essentially a financial impact of marketing outcome. In this case, it is possible that a markdown and promotional campaign may lead to reduction in sales in dollars (profit), if the markdown is too deep. There must be an optimal markdown depth that could maximize the profit of the brand or category. Hence, this study aims to examine the effect of price markdown and promotion, and proposes an empirical approach to derive optimal markdown at consumer segment level.

In practices, retailers frequently use simple metrics such as Regency-Frequency-Monetary (RFM) to segment and profile customers using cluster analysis. Though, it is simple and easy to implement, RFM-based segmentation focuses too much on purchase patterns and driving sales instead of profit maximizing. Several studies have also reported that managers need to rely on intuition and on the long-standing methods—RFM and cross-tabulation (Verhoef et al. 2003). Furthermore, earlier studies on customer segmentation using Finite mixture model mainly used demographic variables as segmentation basis (Gupta and Chintagunta 1994) for campaign management or marketing responses. The most important aspect of our study is that it uses behavioral-based characteristics to segment customers using finite mixture modeling approach. More importantly, the segmentation is based on behavioral-response for profitability and demand model specifically in the context of fashion goods industry. With the abovementioned examples and motivations, the objectives of the study are as follows:

- What are the distinct consumer segments in terms of markdown sensitivities and promotion responsiveness in the context of seasonal goods?
- What is the profitability impact of markdown pricing and promotions upon different consumer segments?
- What are the optimal levels of markdown for each consumer segments for profit maximization?
- What is the optimal target markdown strategy based on the derived profitability segmentation?

We develop an empirical modeling approach to estimate the optimal level of markdown for profit maximization. In particular, we develop profit model based on exponential Poisson-demand specification. The segmentation and response parameters are then modeled and estimated using finite mixture modeling approach. The profit model reveals a classical invertible U-shape relationship between markdown pricing and profitability, and allows us to derive an optimal level of markdown depth.

The overall aims of this study are to provide new insights in following perspectives. Firstly, we provide an empirical strategy for modeling the demand and profitability for seasonal goods industry. The finite mixture modeling approach allows us to identify segment and derive simultaneously the markdown sensitivity of promotion responsiveness. Secondly, the implied methodology in this study allows us to segment consumers based on both demographic and behavioral-based (RFM, cross-buying, and response) characteristics and to employ targeted pricing and promotion strategies. Thirdly, the profitability model provides an approach to derive optimal markdown and assess the potential profit impact at consumer segment level, which provides key implication for optimal targeting strategies based on consumer segmentation.

The rest of this chapter is organized as follows: Section 3.2 reviews the related literatures; Section 3.3 discusses the details of econometric for demand and profit; Section 3.4 introduces the data and variables. Section 3.5 presents the estimation results and discussions of the results; Section 3.6 concludes this chapter.

3.2 Literature Review

3.2.1 Finite Mixture Model

Empirical studies primarily adopt two forms of the approach for segmentation and modeling estimation at segment-level. Firstly, they sequentially use cluster analysis and then estimate consumer responses separately in each of the derived segment. Along with this direction, cluster analysis is a natural approach of identifying consumer segments and modeling consumer heterogeneity. This separation of customers into unique groups is often based on multi-dimensional customer information such as observed customer purchase and usage behavior, demographic and lifestyle characteristics, or even consumer preferences on product and service via self-reported surveys. But this two-step procedure can result in different solutions based on the selection algorithms and variables; there is no theory that can be used to justify the choices of variables and selection algorithm. The second approach is using finite mixture models (a.k.a latent class models or unsupervised learning models) to model unobserved population heterogeneity (e.g., consumer, firm) and uncover hidden relationships (McLachlan and Peel 2004). Specifically, finite mixture model allows researchers to simultaneously derive segmentation and segment-specific weights that relate an outcome (dependent) variable to a set of explanatory (independent) variables and derive a unique estimation model for each segment in a single step (Wedel and Kamakura 2000). Compared to cluster analysis, the finite-mixture model provides statistical tests to determine the number of segments and significance of parameter estimates (Desarbo et al. 2001). More importantly, FMM approach considers individual heterogeneity in response parameters during segmentation, which is not considered in cluster analysis in the two-step approach. The difference in response pattern provides a key difference, especially for behavioral-based segmentation. DeSarbo et al. (2008) have provided a detailed discussion on the comparison of these two approaches.

Finite mixture modeling is getting increasing popularity in the empirical literatures due to the importance of accounting population heterogeneity in the data. For examples, in labor economics, finite mixture model is a popular choice to control the unobserved person-specific individual heterogeneity (e.g., Eckstein and Wolpin (1990) and Keane and Wolpin (1997)). Moreover, Crawford and Shum (2005) used finite mixtures to control the patient-level unobserved heterogeneity while estimating a dynamic matching model of pharmaceutical demand. Gowrisankaran et al. (2008) estimated a dynamic model of voter behavior with finite mixture models in political economics. Several strategic research also use finite mixture model to address firm-level heterogeneity in firm performance (e.g., (Cool and Schendel 1988; Desarbo et al. 2001). In Information Systems literature, the study of Bapna et al. (2011) is the only one that used a finite mixture logit model to classify simultaneously firms into homogenous segments and tested the effects of predictors factors on firms' decision choices of Electronic Payment Systems (EPS) adoption. Comparing multiple model estimates, the study showcases the importance of having segment-based predictive approach in this and other related IS issues. In the last two decades in the marketing literature, finite mixture models have been considered as a dominate approach to address consumer heterogeneity, which is further elaborated in the following section.

3.2.2 Literatures on Consumer Heterogeneity and Sales Responses

In the past decades, extensive marketing studies have investigated the customer heterogeneity in sales response using finite mixture approach. A seminal work by Kamakura and Russell (1989) led to the development of a multinomial logit-mixture model for market segmentation that is based on differences in preferences and price sensitivities across different households. Moreover, Gupta and Chintagunta (1994) proposed an extension of the logit-mixture model that defines prior segment membership probabilities as a function of concomitant (demographic) variables. Jedidi et al. (1997) developed a finite mixture structural equation model that treats simultaneously heterogeneity and forms market segments in the context of a specified model structure, where all the observed variables are measured erroneously. Kamakura et al. (1996) developed a choice model that identifies simultaneously consumer segments on the basis of their preferences, response to the marketing mix, and choice processes. Bucklin et al. (1998) developed a joint estimation approach to segment households on the basis of their responses to price and promotion in brand choice, purchase incidence, and purchase quantity decisions. Bucklin and Gupta (1992) developed an approach for market segmentation based on consumer responses to marketing variables in both brand choice and category purchase incidence. Bayus and Mehta (1995) used finite mixture distribution theory to develop a segmentation model targeting potential consumer durable buyers.

This study follows a similar approach to address the consumer heterogeneity, but aims to contribute to the research area from a perspective of heterogeneous response for the profitability model in the context of seasonal goods. Specifically, our model takes a deep investigation on markdown variables and uses behavioral characteristics as customer-level covariate and responses for segmentation. Moreover, this study directly formulates a segment-specific profitability model, which allows us to assess the profit impact of price markdown at segment-level.

3.2.3 Markdown Pricing and Revenue Management

The literature on markdown pricing strategies focuses three important pricing decisions: (i) what are the goods to offer markdown, (ii) how much to markdown, and (iii) when to apply markdown. Theoretical development of pricing markdown has been addressed in the research literature of marketing, economics and operations research (Eliashberg and Steinberg 1993; Rao 1984;

Rao 1993). Most of the studies on revenue/profit management focus on analytical dynamic pricing of seasonal goods with strategic consumer (Aviv and Pazgal 2008; Bitran and Mondschein 1997; Gupta et al. 2006; Su 2007). A comprehensive literature survey on dynamic pricing by Elmaghraby and Keskinocak (2003) suggests the key characteristics of fashion goods as: 1) Nonreplenishment, 2) Independent demand over time, and 3) Myopic/strategic customer (forward-looking). There are generally two types of markdown pricing: 1) temporary markdown (or sales), wherein prices return to the original value; 2) permanent (e.g., for clearance), wherein the next price can only be lower than the previous one. Majority of the studies address the second type, and it is interesting to study the differential impact of the two types.

There are limited number of empirical studies in operational research, economics, and marketing. The study of Heching et al. (2002) is the only recent empirical one in operational research. They estimated a simple demand model using data from a specialty apparel retailer and obtained parameter estimates of revenues under various pricing policies. The demand specification in this study modeled the season factor and aging factor in a linear demand fashion, which is easy yet intuitive to implement. In economics literature, Warner and Barsky (1995) examined daily prices of eight goods at seventeen retail stores considering weekly and seasonal price patterns, and focused on the frequency of price markdowns on "sales". In the context of Major League Baseball (MLB) ticket prices, Sweeting (2012) showed a significant decline in MLB ticket prices when the time of the game approaches, which is mostly due to declining option values of the sellers rather than changes in elasticity of demand.

Few authors have contributed in the research area of markdown pricing considering fashion retail industry. Gerstner and Hess (1991) showed that manufacturers could stimulate sales by a temporary price reduction, a rebate for consumers or a combination of both. Promotional pricing is characterized by a temporary reduction in prices that revert back once the promotional period is over. As such, these studies do not offer much insight on markdown pricing decisions of fashion goods. Pashigian (1988) provided empirical evidence on sales offered by departmental stores. He gave the growing importance of "fashion" (variety) as an explanation for the changes in markdowns over time and between merchandise groups. Pashigian and Bowen (1991) provided further empirical evidence that demand uncertainty and price discrimination are the two alternative hypotheses to explain the markdown pricing. Hendel and Nevo (2013) offered a simple model of demand dynamics and empirically quantified the impact of inter-temporal price discrimination on profits and welfare. Our study is unique because we directly formulate a segment-specific model to assess the demand and profit impact of markdown. In current perspective, the analysis based on segmentation is lacking in the research area, which this study aims to fill by analyzing segmentation.

3.2.4 Target Pricing and Profitability

There are extensive analytical studies investigating the optimal sales/promotion strategies for profit maximization. For example, Chen and Zhang (2009) investigated whether dynamic targeted pricing based on consumer purchase history could benefit a firm even when consumers are "strategic" (forward-looking). Iyer et al. (2005) compared the strategies of targeted advertising and targeted pricing in a duopoly setting. They concluded that targeted advertising increases profit, and not the targeted pricing. The optimal strategy for targeted advertising consists of maximum advertising targeting to the loyal customers, and less frequently to comparison shoppers. This shows the importance of targetability in the profitability analysis of target pricing.

Many empirical studies have also investigated the impact of target pricing on retailers' profitability. For example, Besanko et al. (2003) explored opportunities for targeted pricing for a retailer that only tracks weekly store level aggregate sales and marketing-mix information. Shankar and Bolton (2004) empirically investigated the determinants of retailers' pricing decisions, and found that competitor factors explained the maximum variance in retailer pricing strategies. A most relevant and recent study is by Soysal and Krishnamurthi (2012), they developed a structural model to estimate a dynamic model of consumer choice behavior in markets for seasonal goods, where products are sold over a finite season and availability is limited.

3.2.5 CRM Literatures in Information Systems and Marketing

Payne and Frow (2005) documented numerous definitions of CRM (see their Appendix). These definitions range from CRM as the implementation of specific system to a holistic approach of managing customer relationships that simultaneously creates both customer and firm value. There is a comprehensive related literature both in Information Systems and Marketing discipline. In Information Systems, researchers focus on technological perspective and economic value of IT at firm level. Firstly, there is a large stream of research on assessing the economic impact of IT investment. For example, several empirical studies (Brynjolfsson 1996; Hitt and Brynjolfsson 1996) focus on how does IT investment impact firm performance, productivity and consumer surplus. There are also many analytical studies investigating IT value on product quality, and cost reduction (Barua et al. 1991; Demirhan et al. 2006; Thatcher and Pingry 2004). Secondly, there are also a large body of studies focusing on the issues on CRM process, implication, and the technology use. For example, Kim & Mukhopadhyay (2011) studied the optimal CRM system implementation strategies. Studies, for instance, of Hendricks et al. (2007), Mithas et al. (2005), and Zablah et al. (2012) focus on enterprise CRM that requires much more expenditure of organizational resources.

In marketing literature, CRM emerges as "relationship marketing" and mainly focuses on CRM strategies. Firstly, the major stream of the studies is focussed on optimizing the marketing mix variables to enhance relationship and customers' lifetime value (Rust and Chung 2006; Rust and Verhoef 2005; Ryals 2005). Secondly, there are several studies (Jayachandran et al. 2005; Mithas et al. 2005; Srinivasan and Moorman 2005) reporting positive effects of CRM investments on customer satisfaction, customer retention or customer life time value. However, this study emphasizes the connection between CRM strategies and profit impact of CRM, which has not been addressed in literature from both the domains.

3.3 Econometrics Model

We use the finite mixture model to derive segment-specific demand estimates and profitability model. Our model of customer purchase behavior aims to capture, at individual-level, the impact of markdown and marketing variables on consumer demand and profitability of category purchase behavior.

The level of analysis is at individuals' category-purchase level for several reasons: First, purchase at category level is common behavior for fashion retailers. For example, the specific product category of a retailer would be replenished with different product (SKU) every business cycle. It is not feasible to study the pricing and marketing activities for a single product (SKU). Thus retailer's revenues and profits are more closely related to category demand than to the sales of any one product (Levy et al. 2004; Nijs et al. 2001). Second, although the impact of promotions can be measured at the either the product (SKU), brand and category level, the category level is the most relevant level for retailers (Ailawadi et al. 2009). Meanwhile, compared with the vast volume of studies pertaining to the effects of price promotions on brand choice and brand sales, research on category-demand effects in a retail store remains sparse (Grewal et al. 2011). Lastly, in terms of profitability impact, maximizing profits at the category level appears to be the basis of most studies on retail pricing behavior (Chintagunta 2002). For example, Pauwels et al. (2002) provided a good example on breakdown of sales in category incidence, brand choice, and purchase quantity.

We elaborate the probability specification of demand and profitability model using FMM in the following two sections.

3.3.1 Segment-Specific Demand Model

Suppose there exists S $(s=1, 2, S)$ segments of consumers in the consumer market. Each segment consists of a number of consumers that are assumed to be similar to each other with respect to their sensitivity and responsiveness of pricing and marketing variables, while those consumers from different segments can differ. In other words, the model specification aims to derive segments of consumers that are homogenous in their sales responses (i.e. members of a segment have a common structural coefficients).

Suppose there are N consumers for the focal firm, each consumer i has made several transactions, each of which consists multiple category purchase incidences. In this case, we denote Ti as number of category purchases during the observation period for consumer i.

Following standard setup of finite mixture model (McLachlan and Peel 2004), the random variable of interest (demand) is assumed to be a draw from a population that is an additive mixture of S distinct segments with proportion (or probability) P_{is} for individual i. The general mixture density of variables can be define by a convex combination of S segments probability density function (pdf)

$$f(d_{ij} \mid \Theta) = \sum_{s=1}^{S} P_{is} \cdot f_s(d_{ij} \mid \theta_s), \qquad (0.13)$$

where $f_s(d_{ij} \mid \theta_s)$ is the pdf of segment s, Θ is the set of parameters to characterize segmentation. P_{is} is the mixing proportions (or probability) that consumer i belongs to Segment s. We then specific P_{is} and $f_s(d_{ij} \mid \theta_s)$ separately as follow.

The segment probability P_{is} is specified to be determined by a vector of consumer-level variables such as demographic or behavioral variables. Following Gupta and Chintagunta (1994) and Vermunt and Magidson (2005), we assume the values of segment memberships follow multinomial distribution, P_{is} can be written as follow:

$$P_{is} = \frac{\exp(\delta_{0s} + \delta_s \mathrm{Z}_i)}{1 + \sum_{s=1}^{S-1} \exp(\delta_{0s} + \delta_s \mathrm{Z}_i)}, \tag{0.14}$$

where δ_s is the segment-specific parameters that captures the effects of individual-specific variables on the probability of segmentation membership (P_{is}), through a non-linear specification. This multinomial-logit specification assumes that $P_{is} > 0 \ \forall \ s = 1, 2, ..., S$, and we have $\sum_{s=1}^{S} P_{is} = 1$ by the specification (Please refer to Gupta and Chintagunta (1994), pp. 130 for details of a similar reformulation of the probability specification).

Individual level Covariates for Customer Segmentation

This study considers consumer demographic and behavioral-based characteristics as covariates for segments (Z_i). The use of demographic variables to predict segmentation has long been used in the literatures (Gupta and Chintagunta 1994) and practice, because the resulted segmentation scheme would be actionable and easier to implement by marketing managers for target marketing. However, the mere uses of demographic variables do not produce satisfactory segmentation due to the problem of incomplete demographic data

(Allenby and Rossi 1998). This problem is particular evident, as the data of this study is from a fashion retail chain from Singapore, where the customer demographic are very similar across segments.

This study focuses on behavioral-based consumer segmentation, which refers to group customer according to their behavioral patterns from purchase history. With the prevalence of CRM system and loyalty program, retailers now frequently capture information on purchase histories and use it to develop pricing and marketing strategies. As discussed previously, Verhoef et al. (2003) showed that RFM is among the most popular segmentation and predictive modeling techniques used by marketers. In this study, we also adopt Regency-Frequency-Monetary (RFM), which is probably the most commonly used descriptive metrics to capture consumers' purchase pattern because of its simplicity and reasonable performance. In particular, three variables represent this past behavior: (1) the period elapsed since the customer's last purchase (Recency; R), (2) the number of purchases in an arbitrary period in the past (Frequency; F), and (3) the total monetary value of purchases (Monetary value; M). Previous studies have shown that RFM alone can offer a powerful way of predicting the future customer purchase (Blattberg et al. 2008; Hughes 2006). Moreover, we also consider using length of relationships (tenure) to capture the relationship aspects of customer characteristics.

Cross buying behavior refers to the purchase of products from multiple categories, which is an important antecedent to consumer-purchase, profitability and loyalty (Reinartz et al. 2008). The rationale behind the stream of literature is that if a customer buys from different categories offered by the same firm, he or she would experience greater attachment to the firm and would naturally has higher demand and profitability. In other words, buyers with cross-buying may aims to maximize the utility obtain from buying from the single retailer. This argument could also been support by transaction cost theory, in which if customers build up switching costs in terms of multiple product ownership (cross-buying), their relationships becomes longer (Rindfleisch and Heide 1997).

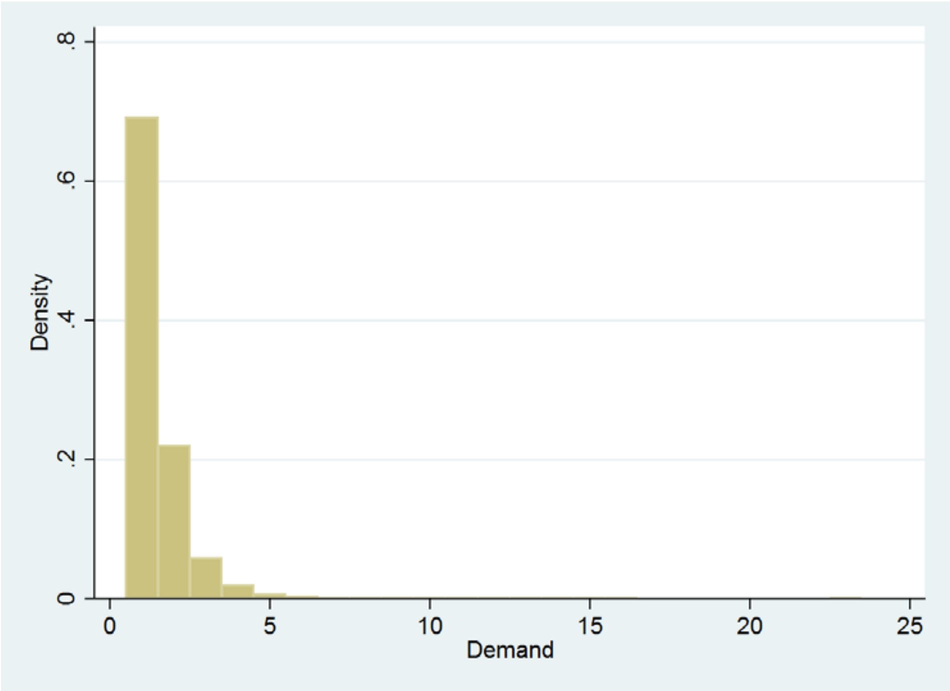


Figure 5 Probability Distribution of Demand

Back to the FMM model specification, the demand of category-transaction conditional on segmentation is then modeled using Poisson demand model due to the nature of demand (See Figure 5 for the probability density of the demand). The segment density functions $f_s(d \mid \theta_s)$ are then assumed to follow Poisson distribution, i.e.

$$f_s(d_{ij} \mid \theta_s) = \frac{\lambda_{ijs}^{d_{ij}}}{d_{ij}!} \exp(-\lambda_{ijs}) \tag{0.15}$$

where

$$\lambda_{ijs} = \exp(\beta_o + \beta_s X_{ij}) \tag{0.16}$$

The vector X_{ij} denotes a set of predictor variables that explain the demand/purchase quantity at transaction level. Specifically X_{ij} contains several variables that specify the transaction demand, which will be discussed as follows.

Demand Function Specification

This study is based on setting of fashion goods industry, in which consumers need to visit the physical stores to purchase goods. With the presence of CRM system, retailers are able to identify the customer and the transaction details at the point of purchase. In this way, we formulate the demand of a purchase incidence as a linear function of several explanatory variables at the transaction level.

First, the level of markdown and the original price of the product naturally determine the demand of category purchase. Consistent with the Poisson specification, we model the demand essentially as an exponential demand function, which is extensively used in marketing and operational research literature (Hanssens and Parsons 1993; Jeuland and Shugan 1988; Song et al. 2008). In such model, the demand response to price markdown follows an increasing returns to scale (see Huang et al. (2013) for a detailed review of demand model), which fits the reality in fashion retail industry, in which a huge bump in sales usually come with a deep markdown. Another advantage of exponential demand specification is the easy of interpretation for policy implication after a log-transformation of demand. Furthermore, we model the markdown depth as the ratio of promotion amount due to markdown over the posted price of the product. For example, a 0.05 markdown is equivalent to an average 5% direct discount offered to a category purchase incidence.

We also include a number of non-price promotion dummies to account for effects other promotional on sales. For example, retailers frequently organized special sales events to advertise the brand and stores. Generally, price-oriented promotions (markdown) are used primarily for their ability to meet short-term objectives such as profit maximization and inventory control, while non-price promotions are used mostly for achieving long-term results such as fostering consumer loyalty. Other than markdown and promotion variables, in apparel retail industries, there are strong seasonal patterns. In this study, we study fashion retailers, which replenish inventory every six months. Within a six-month period, retailer initially charges relative high prices but offers increasingly deep markdown toward the end of the season. As a result, such seasonal price and promotion patterns are likely to cause strategic effects. We include seasonal variables to captures the seasonal impact as a demand shock of seasonal goods. Please note that the empirical context of the study is a retail chain in Singapore, where the traditional four seasons does not appear, but the conventional shopping seasons plays a key role in the seasonal demand pattern.

Last but not list, for the robustness of estimation, we control for unobserved store-specific (locations, size, traffic) and category-specific characteristics (e.g. product design, styles, and colors), which could largely affect the demand. The detailed operationalization of the variables will be discussed in Section 3.4.

In summary, the Poisson rate of the Poisson-like demand can be specify with the following econometric specification:

$$\begin{aligned}\lambda_{ijs} = \exp(&\beta_{os} + \beta_{1s}K_{ij} + \beta_{2s}OP_{ij} + \beta_{3s}PROMO_{ij} + \beta_{4s}SEASON_{ij} \\ &+ \beta_{5s}CATEGORY_{ij} + \beta_{6s}STORE_{ij})\end{aligned} \tag{0.17}$$

where K_{ij} is the depth of markdown, OP_{ij} is the original posted price, $PROMO_{ij}$ denotes a sets of non-price based promotion dummies, $SEASON_{ij}$ is a dummy variable that accounts for whether the transaction is during a shopping seasons such as Christmas. $CATEGORY_{ij}$ and $STORE_{ij}$ are the store and category dummies for controlling unobserved categories and store fixed effect.

One benefit for above demand specification is to allow demand aggregation across items within a category, with the markdown and promotions are all performed at the category level. To see this, suppose now the Poisson demand is at individual product level instead of category, then the Poisson demand can be transformed as follow,

$$\begin{aligned}\lambda_{ijs} &= \exp(\beta_{os} + \beta_{2s}OP_{ij}) \cdot \exp(\beta_{1s}K_{ij} + \beta_{3s}PROMO_{ij} \\ &\quad + \beta_{4s}SEASON_{ij} + \beta_{5s}CATEGORY_{ij}) \\ &= \lambda_{ijs}^{0} \cdot \exp(\beta_{1s}K_{ij} + \beta_{3s}PROMO_{ij} \\ &\quad + \beta_{4s}SEASON_{ij} + \beta_{5s}CATEGORY_{ij})\end{aligned} \tag{0.18}$$

where λ_{ijs}^{0} is the baseline demand at product level when there is no markdown and price is at original price level. In the empirical context of the study, the complete pricing and marketing mix including price markdown and other promotion are specified at category level, which is prevalent in fashion industry as category management. In this case, the specification allows us to aggregate demand at category level by treat λ_{ijs}^{0} as category level baseline demand, as the baseline demand are product-specific.

Please note that in this finite mixture model specification, the covariates alone do not determine the segmentation. Instead, the Poisson regression model plays a major role in predicting segmentation membership. In other words, this prediction/segmentation is based on consumers' demand responses on the sales variables as well as consumer level covariates. In the finite mixture model approach, the posterior classification probabilities do not only depend on covariate, but also the response to dependent variables. Intuitively, the model determines which segment-specific regression model fits best to the responses of an individual consumer. The better that a regression model associated with a particular segment fits, the higher the probability of a customer belonging to that segment. For example, markdown sensitive consumers are assigned to the class for which the regression shows higher markdown effects.

Given the above specification of demand and segmentation probability, the complete likelihood function for the data sample is then given by

$$L = \prod_{i=1}^{N} \sum_{s=1}^{S} P_{is} \cdot \prod_{j=1}^{T_i} f_s(d_{ij} \mid \theta_s) \qquad (0.19)$$

By maximizing the log-likelihood function, the unknown parameters of the model δ_s and β_s can be estimated simultaneously for each segment (Kamakura and Russell 1989; Wedel and Kamakura 2000). Subsequently, each individual customer would be classified to a segment through a posterior probability by choosing the highest posterior probability among segments.

3.3.2 Profitability Model and Optimal Markdown

Profitability Specification and Optimal Demand

Following the similar finite mixture modeling approach in the previous Poisson demand specification, the profitability of transaction is modeled as product of demand by the sales price. Specifically, given the demand specification, the profit function is transformed as follow:

$$\begin{aligned} Profit_{ij} &= \lambda_{ij} \cdot (OP_{ij}(1-K_{ij}) - C_{ij}) \\ &= \exp(\beta_o + \beta_1 K_{ij} + \beta_2 OP_{ij} + \beta_3 PROMO_{ij} + \\ &\quad \beta_4 SEASON_{ij} + \beta_5 CATEGORY_{ij}) \cdot (OP_{ij}(1-K_{ij}) - C_{ij}) \end{aligned} \tag{0.20}$$

where C_{ij} is the marginal cost of goods sold, OP_{ij} is the original posted price and $OP_{ij}(1-K_{ij})$ captured the price after a pricing markdown. The rest of the variables follow the same notation as previous demand model. Due to the limitation of data on marginal cost, we further assume the marginal cost as a percentage of posted prices. i.e. $C_{ij} = l \times OP_{ij}$, where l is the ratio of marginal cost over posted price.

We focuses on Log of profit as dependent variable due to the following reasons: First, the log-transformation of profit allows researchers and practitioners to easily interpretation the profit impact of explanatory variables because of the elasticity nature of the results. Second, the finite mixture modeling requires the underlying probability distribution to be pre-specified with known class of probability distribution. Since distribution of profit is left skewed, the log-transformation made density plot of log (profit) a standard normal distribution, as shown in Figure 6. Lastly, the profitability specification is naturally transformed from a Poisson demand exponential specification from previous section. As a result, the dependent variable is denote as y_{ij} ,

$$
\begin{aligned}
y_{ij} &= \ln(Profit_{ij}) \\
&= \beta_o + \beta_1 K_{ij} + \beta_2 \ln(1-l-K)_{ij} + \beta_3 OP_{ij} + \beta_4 \ln(OP)_{ij} \\
&\quad + \beta_5 PROMO_{ij} + \beta_6 SEASON_{ij} + \beta_7 CATEGORY_{ij} + \varepsilon
\end{aligned}
\qquad (0.21)
$$

This profit formulation has several important properties. First, it reveals the classical inverted U shape relationship between profit and the level markdown down K_{ij} , which is the key decision variable of the study. To see this, the linear term K_{ij} is increasing but the $\ln(1-l-K)_{ij}$ in deceasing in K_{ij} , holding other factors constant. To the best of my knowledge, similar specification has not been discussed in the literature, and we aim to fill the gap by investigating this specification. In this case, as retailer graduate increase markdown, the profit will first increase, then decrease drastically. This specification reflects the demand reality in fashion industry because deep discount is always associated with relatively lower profit, even though it increases demand significantly.

As a result, we are able to derive optimal level or K based on the profit model and parameter estimates. Ceteris paribus, take First-Order-Condition (FOC) of Equation (3.9) w.r.t. K, it is straightforward to see the optimal markdown will be

$$\begin{aligned} K^* &= 1 - \frac{Coefficient\ of\ \ \ln(1-l-K)}{Coefficient\ of\ \ K} \\ &= 1 - \frac{\beta_2}{\beta_1} \end{aligned} \tag{0.22}$$

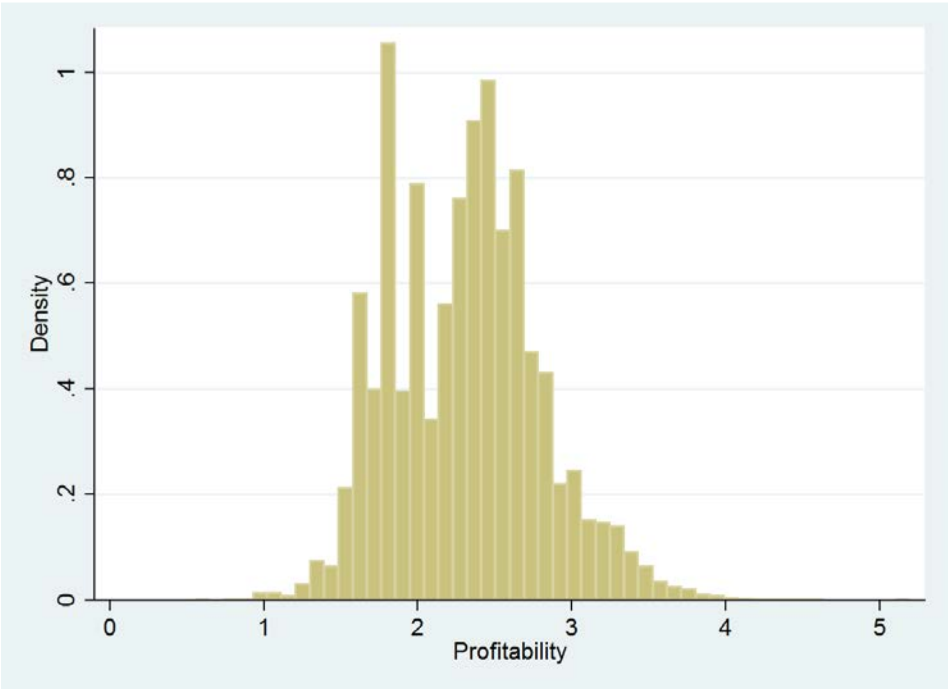


Figure 6 Probability Distribution of Profit

We follow similar model formulation as in the previous section except change the dependent variable to log of transaction profitability with new class of probability distribution. Similarly the general mixture density of variables can be define by a convex combination of S segments pdfs,

$$f(y_{ij} \mid \Theta) = \sum_{s=1}^{S} P_{is} \cdot f_s(y_{ij} \mid \theta_s) \tag{0.23),}$$

where $f_s(y_{ij} \mid \theta_s)$ is the pdf of Segment *s*, Θ is the set of parameters to characterize segments. P_{is} are the mixing proportions (probability) that consumer *i* is in Segment *s*. we use the similar sets of covariates as discussed previous section to predict segment memberships, which follow multinomial distribution, P_{is} can be written as follow:

$$P_{is} = \frac{\exp(\delta_{0s} + \delta_s \, \mathrm{Z}_i)}{1 + \sum_{s=1}^{S-1} \exp(\delta_{0s} + \delta_s \, \mathrm{Z}_i)} \tag{0.24),}$$

Based on the density plot in Figure 6, the segment density functions $f_s(y \mid \theta_s)$ for log-profit *y* are assumed to be normal distributed,

$$f_s(y_{ij} \mid \theta_s) = \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp(-\frac{1}{2\pi\sigma_s^2}(y_{ij} - \mu_{ijs})^2) \tag{0.25}$$

where

$$\mu_{ijs} = \beta_o + \beta_s X_{ij}$$

The dependent variable is thus log (profitability) y_{ij}. The vector X_{ij} denotes a set of predictor variables that explain the profitability at category-transaction level. Generally the explanatory variables is similar as in demand model, but with different functional form following equation (3.9). Specifically, the log-profit can be written as following,

$$\begin{aligned}\mu_{ijs} = \beta_{os} + \beta_{1s}K_{ij} + \beta_{2s}\ln(1-l-K)_{ij} + \beta_{3s}OP_{ij} + \beta_{4s}\ln(OP_{ij}) \\ +\beta_{5s}PROMO_{ij} + \beta_{6s}SEASON_{ij} + \beta_{7s}CATEGORY_{ij}\end{aligned} \tag{0.26}$$

3.4 Data and Variables

3.4.1 Research Background

This study uses data from a major fashion retail chain named FKB[2] located in Singapore. The retailer is specializing in Kids and Baby apparels operating in 32 physical retail stores around the city-state. Due to the stable climate and weather in Singapore all year around, fashion industry in Singapore follows a unique seasonal pattern for demand and sales planning. Unlike many other countries with four-season climate, the seasonality of the demand is mainly driven by the conventional shopping seasons, which are Chinese New Year, Great Singapore Sales in every June and Christmas period. FKB's follows a six-month business cycle throughout the year. The first business cycle starts from January to June, in which the summer school holiday and great Singapore Sales ends. The second business circles starts from July until the Christmas holiday ends. The exact start and end of the season is clearly defined the by FKB in their sales and promotion calendar. Markdown and promotion planning, as well as inventory holding are done for each business cycle ahead of the business cycles to ensure smooth business operation.

FKB sells fashion items across five major product categories, which are Baby Girls, Baby Boys, Kids Girls, Kids Boys and Accessories. The product category

[2] Real name of the retailer is not revealed due to a non-disclosure agreement.

in this study is defined at sub-category level in FKB. For example, we consider "Baby Girl Tee" as a product category instead of "Baby Girl" or "Tee" as product category. The rationale behind this level of analysis is as follows. First, the product in this level of category are extremely similar in terms of product posted price and cost, and are mainly varies in terms of design and colors. Please refer to Appendix D for descriptive statistics of FKB's Top 10 product categories, which justifies the assumption that that the product price and costs are very close within a product category, but difference across categories. Second, there is strong substitution within product category and nearly no substation between the product categories due to nature of product categorization, which eliminates cross-category price elasticity. For example, the price of a Baby Girl Pants is expected to have no impact on demand of Baby Girl Tee. Thirds, FKB are planning and implementing markdown and promotion management at the category level. For example, they would offer 20% discount to certain categories such as "Kids Girl Tee".

FKB has a well-established CRM system through a point-based loyalty program, which currently has over 100,000 members. The CRM system and its loyalty program (LP) have two distinct features. First, LP is designed as a program that allows consumers to accumulate points for future rebates (=6%) when they make repeated purchases with a firm. This feature aims to reward consumers for repeated purchase and foster customer loyalty in the long-run. Second, LP members are eligible for direct discount and markdown during the specific promotion period. In this case, the direct markdown is frequently offered during shopping seasons for competing with other fashion brands or during the end of business cycle for inventory clearance. Moreover, FKB frequency offers various types of non-price based promotion activities for advertising purpose. For examples, FKB organized brand-specific event campaign such as Kids fashion shows, store-opening events and anniversary celebration through large featured and display ads. FKB also actively collaborate with external banks and credit card companies and offer bank-specific promotion offer to consumers.

3.4.2 Data and Variable Operationalization

The data includes the complete and detailed transaction data and member profile data from FKB's CRM system. The observation window is from January 2011 to June 2013. We consolidate the transaction data from CRM data at category-purchase level to identify pricing, demand and profit from Point-of-Sales (POS) and CRM data. Moreover, based on FKB's markdown schedule and promotion calendar, we consolidate a detailed daily promotion dummies and matched them with the category purchase incidences. For the tractability of the analysis, we only include repeated consumers who made at least two transactions during the observation period. To tackle the problem of censoring issue of unobserved transaction outside the observation window, we only include consumers who join the loyalty program within the observation window. As a result, there are in total 9.427 customers in our sample, each of which with an average 8.06 category purchases. The following sections discussed the specification and operationalization of the variables.

Individual Level Covariate for Consumer Segmentation

We include several important demographic variables as explanatory variables. Specifically, age, gender, marriage status are included following the standard operationalization. We also include the nationality as a covariate because about one-fourth of the population in the country are residences with foreign nationalities. As a result, we operationalize the nationality as dummy variable which equals to zero if the customer has a foreign nationality. Moreover, we also include a variable named “opt-in” to capture whether the consumer is willing to receive newsletter and promotion message via mail, email or SMS. The “opt-in” is thus takes value from 0 to 3, indicating consumers’ attitude towards the marketing communication.

The Behavioral-based covariate includes RFM and cross-buying variables. Specifically, based on the historical purchase data, we measure the recency as the time elapses (in weeks) since last purchase to the last day of observation windows. Frequency is measured by the average frequency of purchases, i.e. the average number of transaction per week. Monetary value refers to the total dollar amount during the past six months, the standard business and product lifetime cycle. Lastly, we also include a relational variable “tenure” as the number of days since the customer becomes a loyalty program member. The cross-buying variables are operationalized with two variables following a study by Reinartz et al. (2008). The first measure is the “width” of cross-buying is the average the total number of distinct product categories from which he or she has purchased per transaction. In this case, it captures the width of the cross-buying behavior. The second variable captures the dispersion of spending across categories. Suppose there are two customers who buy from three different product categories. However, one person spread the purchase evenly across the three categories, while the other primarily buy from one single product category and spend very less from the rest of the two categories. In this case, a measure called “balance” of the cross-buying measures the degree of spread (or concentration) of spending across the categories. Specifically, we computer the purchasing share percentage for all product categories and then derive the standard deviation of these share percentage. In this case, customer exhibits high concentration of purchase behavior (purchases predominately in one category) if the balance value is high.

Markdown and Promotion Variable at Transaction Level

As discussed previously, the pricing, promotion variables are constructed at transaction level. Specifically, the markdown variable is constructed by the percentage of markdown that is offered to consumer for the category-purchase, and is a variable from zero to one. The non-priced promotion dummies are generated from the FKB’s marketing and promotion calendar, which determines the promotion activities ahead of a six-month business cycle. In particular, we include sales events (e.g. Fashion Shows, Brand Anniversary, and Store-opening), and collaboration promotion with Banks as the promotion dummies variables at transaction level.

We include several key control variables for controlling other unobserved factors that affect demand or profit. In particular, we add category dummy variables for category fixed effect and store dummies to store-specific factors. We also include seasonal dummies to capture the seasonality of consumer purchase behavior. In this model, we code seasonal dummy as one if the purchase occurs during Christmas, Great Singapore Sales (in June) and Chinese New Year period. For the ratio of posted price to marginal cost (l), we consider $l=0.2$ based on the product-level descriptive data (See Appendix D for example). We will test the sensitivity of this cost assumption in the later section for robustness check.

3.5 Results and Discussion

3.5.1 Estimation Results for Demand Model

We use Latent GOLD® 4.5 (Vermunt and Magidson 2005) for the Maximum Likelihood Estimation (MLE) procedures. Other statistical package such *R* with *FlexiMix* framework and Stata also provide implementation of finite mixture model. Latent GOLD provides a user-friendly interface and a fit to our model specification, and has also been widely used in literature (e.g. Bapna et al. (2011)). In particular, a latent class regression module is used to identify segment-specific estimates and model selection procedures.

To estimate the parameter Latent GOLD uses both the Expectation maximization (EM) and the Newton-Raphson (NR) algorithm, which are seemingly the most popular technique used to determine the parameters of a mixture with an a priori given number of components. All estimations are using robust-standard errors.

Model Selection

Determining the number of segment a finite mixture model is a critical model selection issue. Theoretically, specifying too few segment ignores segment differences, while too many segment results in unstable segmentation and estimates. In ideal case, the model selection requires the researchers' priori knowledge of the populations' structures, in which they can compare the model directly using statistics such as likelihood ratio test. In most practical cases and previous studies, however, the actual number of segments *S* is unknown and must be inferred from the data itself. The most commonly used criteria bases on the goodness-of-fit measure and quality of classification using entropy-based measure. Please refer to Appendix E for a detailed technical discussion of the two criteria.

In this study, we report various information criteria and quality of classification (Entropy-based Measure) to choose the acceptable number of segments. Following the common procedure, we estimate the finite mixture model for different value of *S*. The information criteria values for each value of s are listed in Table 2 in Appendix F. The measures generally suggest a two segment solution is a reasonable one for segmentation based on demand model, as AIC tends to over-cluster the data (Naik et al. 2007). Moreover, the entropy-based measure of two segments is 0.59, and decreases with more or less segments, which indicates a generally good separation of the 2 segments. The pseudo-R^2 increases from 0.11 to 0.15 for selected solution.

The descriptive statistics for two segment mixture model is presented to evaluate the quality of segmentation. The classification of segmentation is based on posterior segment membership probabilities derived from the multinomial logit model. In other words, a consumer is classified as in Segment X if his resulted posterior segmentation probability for Segment X is the highest among all segments.

Table 2 Descriptive of Demand-based Segmentation

Variable	Segment Mean 1	2
Demand	1.441	2.092
Covariates		
Age	36.381	38.864
Female	0.895	0.873
Local (Nationality)	0.763	0.615
Marital Status	0.916	0.881
Opt-in	2.786	2.927
Cross-Buying Width	2.140	1.978
Cross-Buying Balance	0.063	0.043
Tenure	575.983	601.590
Regency	22.055	24.710
Frequency	0.010	0.015
Monetary	83.369	140.586
Segment Size	0.683	0.317

Generally, the segments are segmented by several key variables such as tenure, local (nationality, marital status, and regency of last purchase. The relative size for each segment is relatively large (0.683 and 0.317), indicating the segmentation is sustainable (Wedel and Kamakura 2000). In particular, Segment 1 is characterized as consumers with relatively low demand, higher cross-buying, but low RFM value. In contrast, Segment 2 consumers can be characterized as high demand, lower cross-buying, higher monetary and older consumers. Generally, such significant segments represent an important contribution of the study, because we clearly see cross-buying and behavioral characteristics are more effective covariates for consumer segmentation, compared to demographic variables. The demographic variables are generally similar across two segments, which will be further validated in the parameter estimates in the results of multinomial logit in the later paragraph.

Table 4 shows the finite mixture model solution with 2 segments. A standard Poisson panel regression is presented for the baseline comparison. The Segment prediction model refers to the multinomial-logit segmentation model, which shows the covariate estimates for determining the segment of consumers. Figure 7 shows the decomposition of the mixture density function based on segmentation.

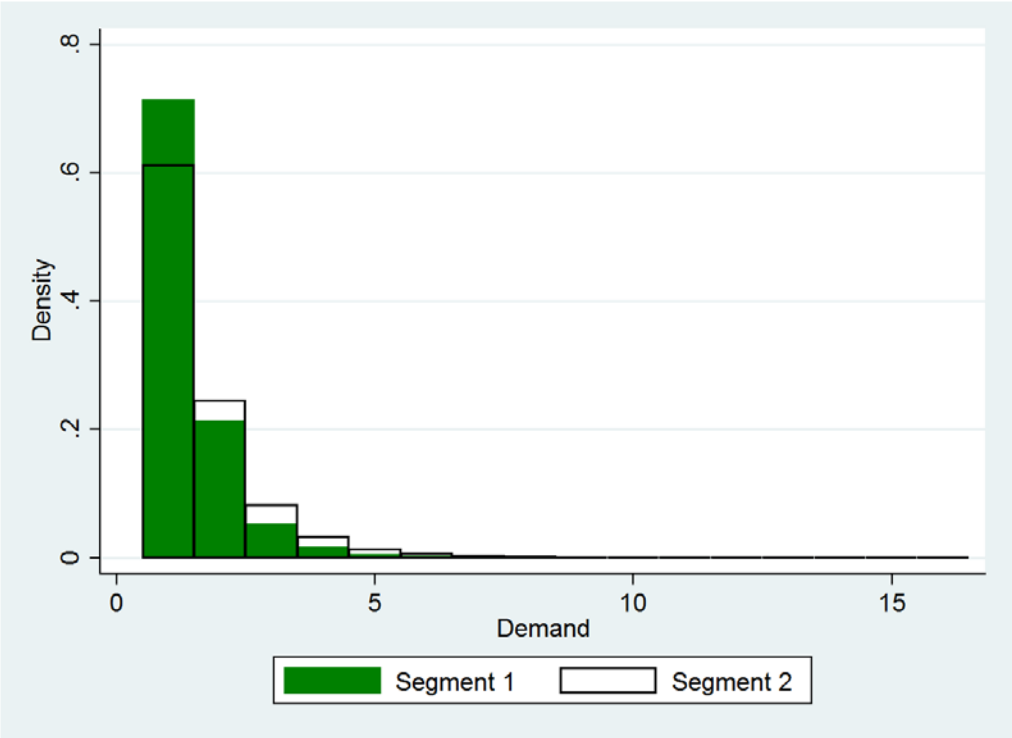


Figure 7. Mixture Distribution of Demand Estimates

In Table 4, we report Wald statistic to test whether overall segment-specific effects are significant for parameter estimates. A separate Z-statistics are computed to test the significance of each individual segment-specific parameter. Moreover, a Wald (=) statistic are reported to test the equality of each set of regression effects across classes. In other words, it tests whether regression coefficients are equal between segments (testing the null hypothesis of equality of parameter estimates).

Table 3 Estimation Results for Demand Model

Model Variable	**Poisson Regression**	Segment **1**	**2**	**Wald**	**Wald(=)**
K	0.350***	0.327***	0.600***	593.520***	8.418***
OP	-0.009***	-0.009***	-0.015***	311.025***	3.862**
Event	0.004	0.006	-0.009	0.284	0.038
Bank Promo	0.006**	0.005*	0.041**	8.013**	2.964**
Season	0.011***	0.010***	0.047***	19.203***	3.934**
Intercept	0.386***	-0.466***	0.624***	187.013***	60.097***
Segment Prediction Model					
Age		-0.027***	0.027***	11.336***	
Female		-0.007	0.007	0.004	
Local		0.205***	-0.205***	9.213***	
Marital Status		0.137	-0.137	1.739	
Opt-in		-0.401	0.401	0.846	
Cross-buying Width		0.058	-0.058	0.248	

Cross-buying Balance		10.431***	-10.431***	17.917***
Tenure		-0.001	0.001	1.712
Regency		-0.008***	0.008***	7.177***
Frequency		-11.523*	11.523*	3.607*
Monetary		-0.002***	0.002***	19.386***
Intercept		3.980***	-3.980***	7.038***
Pseudo- R^2	0.044	0.122	0.239	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Generally, markdown variables are generally significant based on Z-statistics and Wald Statistics. Compared to Segment 1, Segment 2 consumers are more sensitive to markdown and promotional activities. They are also more sensitive to the seasonal timing of purchase, i.e. more sensitive to seasonal variables. The results also include category and store fixed effects that are not reported here. Generally, both category fix effect (Wald=) and store fixed effects (Wald=) are significant.

Results of Wald (=) statistics is to test the between-segment difference of response parameters (test the null hypothesis of equality). An insignificant Wald (=) statistic means that the two segments responses to the same degree. The results generally show that the cross-segment effect is not significant. The reason is partly due to the fact the number of segment derives is relatively small.

The parameter for multinomial-logit model is reported under the heading “Segment Prediction Model”. Overall, the Wald statistics in segment prediction model shows the parameters for behavioral-based variables and cross-buying variables are significant, and the estimates for demographic variables are not (expect for age). In other words, behavioral-based characteristics (RFM, tenure) and cross-buying variables can effectively segment customers, compared to segmentation using demographic variables.

3.5.2 Estimation Results for Segment Profitability

Similarly to previous estimation of demand model, we present the segmentation and parameter estimates for profitability function following the model specification in Section 3.3.2.

The model selection procedure is also based in information criterion, quality and classification. Table 5 reports the value of information criteria, Entropy-based measure and Pseudo-R^2. The information criteria suggests that four-segment solution is the best model, based on BIC and CAIC. For quality of segmentation, the four-segment solution gives us the highest Entropy-based measure (0.71), which shows good separation of segments. The pseudo-R^2 is 0.59 is the highest among alternative solutions.

The Table 6 reports the classification based on the posterior segment probabilities derived from the four-segment solution. First the relative size for each segment is large, indicating the segmentation is sustainable (Wedel and Kamakura 2000). Specifically, based on covariates, Segment 1 and 4 are characterized by relatively medium profitability. Even through Segment 1 is largest segment (47.3%) and Segment 4 (1.5%) is the smallest, Segment 1 has significantly higher value in terms of cross-buying and behavioral characteristics. On the other hands, Segment 2 (46.6%) and Segment 3 (4.5%) are high and low profitable consumers respectively. Note that the high profitable Segment 2 has significant less cross-buying than other segments. Generally, the demographic characteristics are very similar across the 4 segments, which will be further validated based the responses and parameter estimates in the profit model.

Table 4 Descriptive of Profitability-base Segmentation

	Segment Mean			
Variable	**1**	**2**	**3**	**4**
Log(Profit)	1.834	2.011	1.677	1.810
Covariates				
Tenure(days)	587.830	570.175	523.346	583.811
Age	35.773	37.086	36.657	36.964
Female	0.898	0.895	0.887	0.805
Local	0.779	0.736	0.800	0.752
Marital	0.919	0.920	0.850	0.871
optin_level	2.796	2.786	2.714	2.878
avg_no_cat	2.240	2.054	1.959	1.950
avg_balance_cat	0.068	0.056	0.067	0.064
Frequency	0.010	0.011	0.010	0.007
Monetary	82.823	91.250	54.036	41.372
Recency(weeks)	21.087	22.327	28.647	28.711
Segment Size	0.473	0.466	0.045	0.015

Figure 8 shows the decomposition of the mixture density function of profitability based on segmentation.

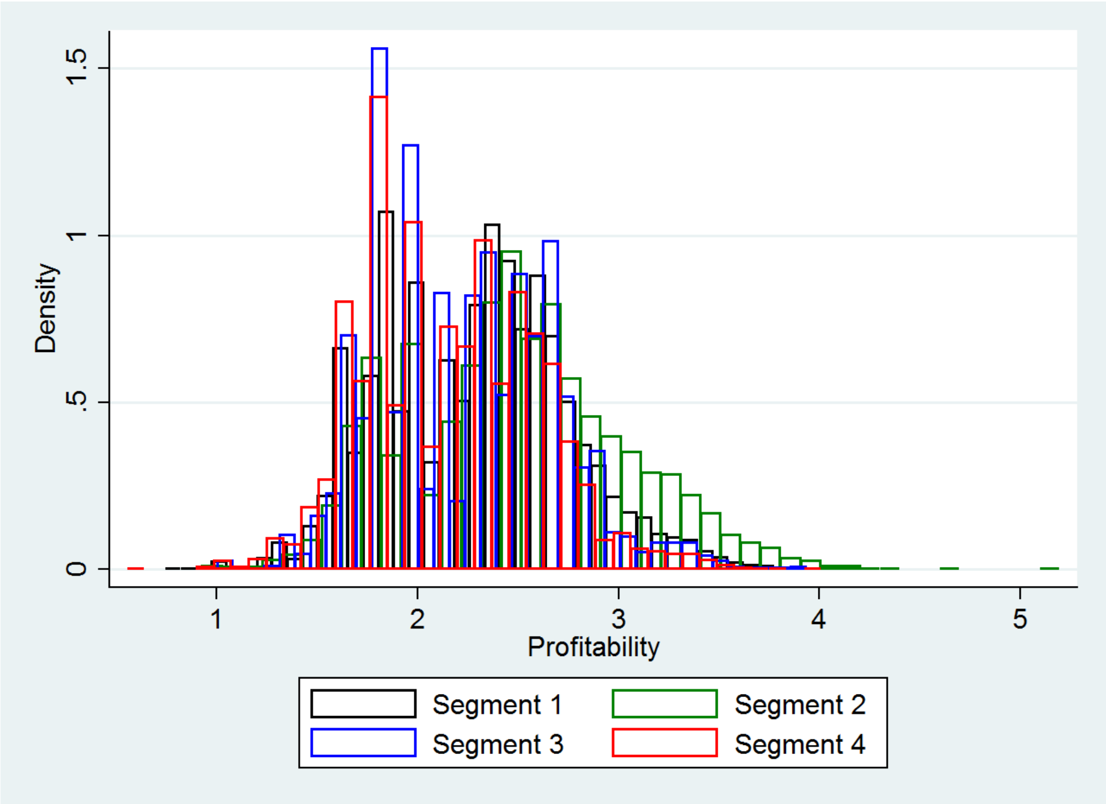


Figure 8 Mixture Distribution of Profitability Model

Table 7 presents the parametric estimates of four-segment mixture regression. We also present a standard OLS estimates to compare with the segment-specific estimation results.

Table 5 Parameter Estimates of Profitability Model

Variable	OLS	Seg 1	Segment Seg 2	Seg 3	Seg 4	Wald	Wald(=)
K	3.519***	3.020***	4.178***	1.494***	1.903***	37632.60***	3903.61***

Log(1-l-K)	2.879***	2.591***	3.288***	1.646***	1.956***	79200.70***	3748.52***
Log(OP)	0.805***	0.815***	0.820***	0.865***	0.863***	86612.87***	8.355**
OP	-0.002***	-0.001	-0.004***	0.002***	0.002***	460.24***	49.39***
Event	-0.005	-0.003	-0.010	-0.001	0.313***	-0.00***	4519.72***
Bank	0.002	0.004**	-0.002	0.000	0.000	7.40	6.591*
Season	0.009***	0.003	0.017***	0.000	0.000	55.33***	54.072***
Intercept	-0.27***	-0.710***	0.091	-0.800***	0.065***	13865.53***	1352.56***
Segment Prediction Model							
Age		-0.014***	0.007*	0.001	0.005	25.50***	
Female		0.107**	0.106**	0.050	-0.263***	8.67**	
Local		0.049	-0.100***	0.097	-0.046	19.95***	
Marital Status		0.181***	0.111**	-0.207***	-0.085	20.53***	
Opt-in		-0.059	-0.061	-0.183*	0.303	3.82	
Cross-buying Width		0.535***	0.128**	-0.354***	-0.308**	120.77***	
Cross-buying Balance		2.360***	-6.274***	3.061**	0.854	91.58***	
Tenure		0.002***	0.001***	-0.002***	-0.001**	111.29***	
Frequency		45.971***	32.721***	23.898**	-102.590***	34.26***	
Monetary		0.001	0.003***	-0.002*	-0.002	52.07***	
Recency		-0.010***	0.001	0.011***	-0.001	52.24***	
Intercept		-0.614*	0.419	0.661	-0.466	14.72***	
Pseudo- R^2	0.42	0.644	0.478	0.990	0.990		

Generally, the results show distinct pricing and promotion responses across customer segments. For the main model estimation, the Z-statistics and Wald statistics are highly significant for all explanatory variables (except for bank promotion). However, even though the Wald statistics are significant for all parameters, different segments has distinct response pattern. For example, Segment 1 and 4 (with relatively medium profitability) are very similar in terms of descriptive statistics, but Segment 1 is more responsive to bank promotion but Segment 4 is more responsive to promotional events. In this case, Segment

1 can be labeled as “Medium profitable, promotion sensitive” segment and Segment 4 can be labeled as “Medium profitable, events buyer” segment. Moreover, the Segment 2 with high profitability can be characterized by highly sensitivities to seasonal factors but insensitive to non-price promotion activities. In other words, Segment 2 can be labeled as “high profitable, seasonal buyer” segment. Finally, Segment 3 with low profitability is mainly characterized by covariate with low RFM value.

Wald (=) statistics for testing the between-segment difference is also reported. The results show significant response coefficient for pricing, seasonal and promotion variables. The results indicate strong cross-segment difference in parameter estimations.

In terms of Segment prediction model, although Wald statistics suggests that demographic variables are overall significant (except for opt-in) in predicting segmentation, it is not obvious based on the descriptive statistics in Table 6. Generally, based on the Wald test and Z-statistics, we see cross-buying variable and behavioral-based covariates have much stronger predicting power for segmentation.

In the above analysis, we present two segmentation schemes: demand-based and profitability-based segmentation. Intuitively, high sales in unit (demand) does not necessarily mean high profitability (Shapiro et al. 1987). Profitability captures not only the positive “demand-effect” due to markdown but also the negative impact of reduced profit-margin per item. In our analysis, based on our analysis, profitability-based segmentation provides a more-detailed segmentation, which allows for more detailed classification and improved targeting strategies.

In fact, most previous studies in marketing only focus on the impact of price-promotion on sales in terms of demand or sales quantity (Please refer to Section 3.2.2 for related literature). From practitioners' perspectives, the choice of these two critically depends on the business objectives. For example, demand-based segmentation could be only effective if retailers have inventory pressure to clear the stock near the end of the business-cycle.

A significant implication of the profitability model is to allow us to derive the optimal markdown level, following Equation (3.9) and (3.10), we are able to derive the optimal level of markdown, as reported in Table 8. The detailed of associated profit impact are discussed in the next section.

3.5.3 Profit Impact and Optimal Target Markdown

In this section, we analyze the sales response to markdown pricing of customer category purchases to show how the profitability model can be used to optimally offer target markdown.

First, follow Equation (3.10), the optimal level of markdown for each segment is reported in Table 8 for each consumer segment. Generally, the retailer should offer higher level markdown for high profitable segment (Segment 1 and 2) and low (or no) markdown to low profitable consumer segment (Segment 3 and 4). This is consistent with the conventional wisdom that retailers should offer more markdowns for their profitable or loyalty consumers to in order to extract higher profit.

Given the customers' posterior segment membership probabilities generated from the finite mixture estimation of profitability model, we can predict the expected profit-contribution as a weighted average of segment-specific profit. Given the segmentation profile, we consider the model-predicted profit with markdown=0 (price set at posted price) as the baseline profit at individual and segment-level, assuming the other marketing conditions (marketing mix, seasonality etc.) remains the same. We consider several scenarios for different common values (e.g. 5%, 10%, 15%, 20%, 25%, 30%, 35%, and 40%) of markdown offered in different scenario. In practice the different values can be achieved by offering a direct in-store discount or issuing coupon. We then derive the new profit generated based on the segmented parameter estimates for each individual consumers. Lastly, weighted by individuals' posterior segment probabilities, we predict the new segment profit. Then the segment-specific/overall profit impact is given by the difference between new profit and baseline profit, divided by baseline profit.

Table 6 Profit Impact of Target Markdown Strategy

	Segment-Specific Profit Impact (%)				Targeting Strategies		
Scenario	Seg 1	Seg 2	Seg 3	Seg 4	Optimal Targeting	Non Targeting	Profit Potential
5% off	1.82%	4.10%	-0.97%	-0.52%	2.77%	2.72%	0.05%
10% off	2.94%	7.39%	-2.37%	-1.57%	4.83%	4.70%	0.13%
15% off	**3.23%**	9.66%	-4.24%	-3.19%	6.03%	5.79%	0.24%
20% off	2.61%	**10.71%**	-6.61%	-5.43%	**6.23%**	**5.85%**	0.38%

25% off	0.95%	10.34%	-9.51%	-8.33%	5.27%	4.72%	0.55%
30% off	-1.81%	8.38%	-12.96%	-11.91%	3.90%	2.28%	1.62%
35% off	-5.76%	4.67%	-16.98%	-16.19%	2.18%	-1.56%	3.73%
40% off	-10.93%	-0.86%	-21.58%	-21.18%	0.00%	-6.86%	**6.86%**
Segment Size	0.473	0.466	0.045	0.015			
Optimal Markdown	**0.14**	**0.21**	0	0			

Table 8 reports the profit impact in percentage term comparing to baseline level for different markdown scenarios on the four segments solution that we derived from profitability model. The result provides key insights from several perspectives on target markdown strategy.

First, at segment level, the profit impact reveals how retailers should target to an individual consumer segment. For example, if a retailer is interested in only offering target markdown to Segment 1, the best strategy is to choose 15% among all the markdown scenarios; whereas the optimal markdown scenario for Segment 2 should be 20%. This is straightforward as the optimal levels of markdown from model are 0.1 and 0.21 for Segment 1 and 2. Moreover, the profit impact for Segment 3 and 4 are always negative in all scenarios. In other words, the retailer should not offer any markdown to these two segments as the profitability monotonically decreases with markdown depth.

Second, we consider a targeting strategy, in which the retailer only offers a flat rate of markdown and no targeting is implemented. In other words, the retailer would offer the same level of markdown to all four consumer segments.

The corresponding overall profit impacts for all segments are reported under the column “non-targeting”. The number is essentially the aggregate profit impact for all segments, weighted by the size of the consumer segments. In this case, we see the best scenario with highest overall profit impact (6.23%) is the scenario with 20% markdown.

Third, with the detailed segment-specific profit impact, the retailer can choose to only target to those profitable segment (profit impact>0) for each scenario. In this case, we can derive the overall profit impact of this “Optimal Targeting” on segment, which is presented in the table. The results show that the “20% off” scenario has the highest profit impact. Moreover, we also report the difference of profit impact between “non-targeting” and “optimal-targeting”, in order to quantify the economic value and impact of the targeting strategy. This difference can be also understood as the profit potential of target markdown strategy. Clearly, the profit potential increases with the level of markdown, which is consistent with the theoretical understanding on target pricing. Figure 9 presents the how the profit impact changes when the level of markdown changes, for all the four segments, as well as for the “non-targeting” and “Optimal targeting” cases.

Please note that the optimal targeting is not feasible due to the probabilistic nature of the finite mixture model. The consumers are assigned to a segment with the “largest probability” from the segmentation. For example, it is possible that a consumer is classified in Segment 1 but his/her actually belongs to Segment 2 in really. In this case, the target markdown pricing could be offered to the incorrect segment, which reduces the profitability. As a result, the profit potential would increase when the quality of segmentation improved. In the extreme case when the misclassification is zero, the optimal profit impact can be achieved.

The marketing cost of targeting is omitted in this analysis for the ease of exploration. However, in practice it can be specified as the per-unit cost which is proportion to segment size. I.e. targeting larger customer segments incurs more marketing costs on targeting. In this case, the retailer needs to compare the profit impact with targeting cost through cost-benefit analysis to decide whether to target a specific segment.

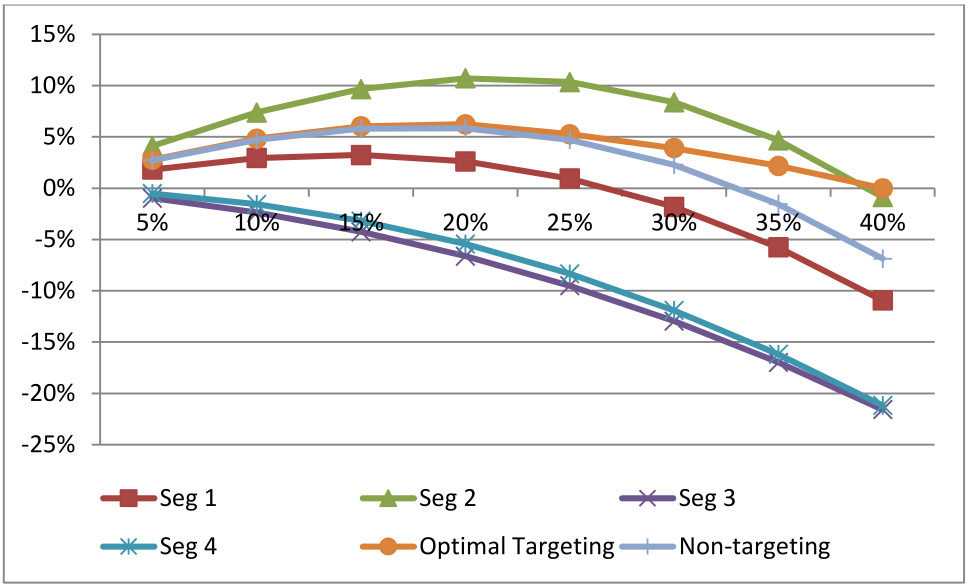


Figure 9 Profit Impact of Target Markdown

The method to assess profit impact at segment level provides a simple decision heuristic for optimal targeting markdown; we summarize this simple procedure to optimal targeting as follows:

1. Estimate segment-specific profitability Model using Finite-Mixture Model Approach.
2. Decide number of segments by information criterion and classification quality, and derive the optimal markdown as guideline.
3. Compute baseline profit by assuming no markdown policy is offered.
4. For each possible markdown policy (e.g. 5%, 10%, 15%), derive segment-specific profit impact.
5. Compute the overall potential profit impact by only targeting on profitable segment and choose the targeting markdown strategies with the highest profit impact.

Please note that with the estimation of the segmentation and profitability model, a similar procedure can be performed to assess the segment-specific and overall profit impact for other promotion activities. For example, the scenario of this would be one for other promotional activities and campaigns.

3.5.4 Robustness Check

Profitability-based Model Selection

So far we follow the standard procedures in the literature using information criteria and entropy-based measure for model selection procedures. The existing procedures purely based on goodness-fit measure thus it is data-driven and not necessarily profit-maximizing. Assuming the alternative models with different number of segment are also “true” model, we are able to verify the model selection using the profit impact measures. In other words, we are interested in whether the model selected is indeed the profit-maximizing solution. As the model selection information criteria are relatively close between solutions, it is necessary to examine the profit impact for each solution. Therefore, we report the optimal level of markdown, as well as their size for the respective segments in each solution. Based on similar procedures in the previous section, we are able to derive the profit impact in a hypothetical case, in which retailer set the segment-level markdown at the optimal level. Table 9 presents the solutions including optimal level of markdown (*K*) and segment size and overall profit impact when optimal markdown is offered for each segment for alternative solutions.

Table 7 Profitability-based Model Selection

Model Solution	**Optimal *K* and Segment Size**	**Profit Impact at Optimal *K***
1-Segment	0.18, 100%	6.41%
2-Segment	0.21,54.0% 0.13,46.0%	6.53%
3-Segment	0.21, 48.2% 0.14, 46.1% 0, 5.7%	6.5465%
4-Segment	0.14, 47.3% 0.21, 46.6% 0, 4.5% 0, 1.5%	**6.5508%**
5-Segment	0.16, 53.4% 0.24, 20.7%	6.51%

0.13, 20% 0, 5.7% 0, 0.2%	

Based on the results in Table 9, we see that that the 4-sgement solution still gives us the highest potential profit impact. The best markdown scenario (similar in previous section) for each segment solution is all 20%. Overall the higher markdowns are offered for customer with higher profitability.

Intuitively, as we discussed, specifying too few segment ignores segment differences, while too many segment results in unstable segmentation and estimates. Overall the profit impact increases from 1-segment solution to 4-segment solution at maximum then has a significantly drop in the 5-segment solution. Compare to the model selection criteria presented in Table 5, we observed that the trend is generally aligned with the entropy measure for quality of classification. Recall that the entropy-based measure captures the degree of separation based on derived posterior segment probability. The entropy measure gives an aggregate value of how strongly customers belong to one particular segment. Given number of segment *S*, Entropy-based measure will be zero when all posterior segment probability are equal for each cross-session (maximum entropy). This is consistent with the theoretical understanding that the targetability (Chen and Iyer 2002) determines the potential of profit impact. For example, if the segmentation can better classify the consumers, it will have higher profit potential.

Overall, the result highlights the importance of the quality of segmentation (entropy-base measure) as the primary factor to determine the profit impact of segment solutions. Previous studies tend to over emphasize on using information criteria as heuristics for model-fit. This finding shows that profitability-based model selection could be more useful consideration; especially when the objective is profit-maximization and no significant differences in goodness-of-fit measure in alternative models are observed. From practical point of view, this consideration could also be more valuable to retailers as the profit impact is usually the key objective in segmentation.

Sensitivity Analysis to Cost Assumption

In order to see whether the model and results are sensitive to the assumption on marginal cost, we re-estimate the model using by assuming the marginal cost as 30% of posted price. As a result, a similar four-segment solution is reported in Table 10

Table 8 Profit Impact for Alternative Cost Assumption

	Segment-Specific Profit Impact (%)				Targeting Strategies		
Scenario	Seg 1	Seg 2	Seg 3	Seg 4	Optimal Targeting	Non Targeting	Profit Potential
5% off	2.35%	7.56%	-1.54%	-0.53%	4.15%	4.01%	0.14%
10% off	**3.55%**	13.65%	-3.72%	-1.92%	7.10%	6.66%	0.44%
15% off	3.43%	17.72%	-6.58%	-4.25%	**8.54%**	**7.64%**	0.90%
20% off	1.82%	**19.27%**	-10.15%	-7.56%	8.20%	6.67%	1.53%
25% off	-1.39%	17.83%	-14.42%	-11.86%	5.84%	3.51%	2.34%
30% off	-6.25%	13.14%	-19.39%	-17.15%	4.89%	-1.98%	6.87%

35% off	-12.75%	5.12%	-25.05%	-23.39%	1.90%	-9.80%	11.71%
40% off	-20.79%	-5.98%	-31.34%	-30.50%	0.00%	-19.80%	19.80%
Segment Size	0.569	0.372	0.045	0.014			
Optimal Markdown	**0.12**	**0.20**	0	0			

Overall, the results are similar to the main analysis in Table 9. The optimal markdown for Segment 1 and 2 reduced from 0.14, 0.21 to 0.12 and 0.20 respectively, which are consistent with the theoretical intuition. In other words, the optimal markdown should be generally decreases with the increasing marginal cost. Moreover, we generally observed that the profit impact is generally more sensitive to markdown scenarios and different target strategies, which is also consistent with theoretical understanding.

3.6 Conclusion

In this study, we proposed segment-specific demand and profitability model that can be used to identify optimal markdown policy and targeting strategy in fashion goods industry. In particular, we developed a customer profitability model and segmentation strategy based on customers' demographic and behavioral-based characteristics and sales responses. By using the CRM data on members' profile and their detailed transaction data, along with marketing/promotion plans of a fashion retail chain in Singapore, we used finite mixture model and estimated the impact of markdown and promotions on consumer demand and profitability. The analysis shows significant differences in pricing and promotion variables across the consumer segments. The derived profitability-based segmentation allows us to investigate the profit impact of pricing and promotion and provide key implication on the optimal targeting strategy at consumer segment level.

3.6.1 Implication for Research

This study aimed to contribute to the existing research from three perspectives. Firstly, this study makes a significant contribute in the research on consumer heterogeneity in sales responses. In particular, we considered behavior-based variables as covariates for segmentation; while earlier studies mainly used behavioral-based approach via cluster analysis for segmentation. However it has been largely ignored when applying finite-mixture modeling. Moreover, earlier studies also showed that demographic-based approach is not very effective in FMM-based segmentation (Allenby and Rossi 1998). Given the modeling advantage of FMM, our analysis demonstrated how behavioral-based characteristics and responses from CRM can be effectively used in FMM-based segmentation. We also took into account seasonality as a critical covariate in capturing the seasonality-nature of consumer demands in fashion goods market.

Second, this study focused on markdown pricing at segment-level, which had been largely ignored in markdown pricing studies, especially in an empirical context. On the one hand, existing studies on target pricing literatures are analytical, wherein consumer segments are often exogenously and explicitly assumed (e.g., (Chen and Zhang 2009)). On the other hand, empirical studies largely ignored consumer heterogeneity in the investigation of markdown pricing for fashion goods (e.g., (Heching et al. 2002)).

Last but not least, from methodological point of view, our modeling procedure provides an empirical approach to determine the consumer segmentation and optimal markdown simultaneously. Subsequently, the analytical approach and profitability model can be used to determine the optimal level of markdown for consumer segments, which has key practical implications. This approach can offer critical insights for retailers for target markdown and promotion strategies. For example, for different markdown and promotion scenarios, our analysis showed different profit impacts for each segment and overall consumer population. Our analysis provided not only in-depth understanding about markdown pricing and profitability, but also actionable targeting strategy based on profit impact. Most of the literature in marketing focuses on the selection of promising customers as target for a promotional campaign, but much less is on addressing what specific offers to be directed to the target groups (Reutterer et al. 2006). This study fills this important gap by focusing the profitability analysis at consumer segment level.

3.6.2 Implication for Practice

Based on the profitability analysis and segmentation, this study can help retail managers to identify the high profitable/demand segment through more effective segmentation and offer targeted markdown and promotion strategies accordingly. Firstly, with the ubiquity of CRM implementation and availability of consumer-level historical data through CRM system, retailers are able to measure customer characteristics in several dimensions. These dimensions include not only consumer demographics, but also behavioral-based characteristics, and sales response to price and non-price promotions in terms of profitability. The new segmentation-based approach used in this study can provide more new perspectives such as product category analysis (Andrews and Currim 2002) through cross-buying behavior for retail mangers to design corresponding pricing and promotion activities (e.g., cross-selling).

Secondly, our analysis provided segmentation and response analysis for both product demand and profitability. Comparing these two schemes, profitability-based segmentation provides more detailed segmentation because it captures both the demand effect and price margin for a markdown pricing scenario. Intuitively, a high sale-volume does not necessarily mean high profitability. In practice, the choice of the two segmentation schemes could be based on the business objectives of firms. For instance, retailers can prefer to use demand-based segmentation, when facing inventory consideration near the end of the business cycles or seasons. Meanwhile, suppose if the two markdown scenarios produce similar profit impact, demand-based segmentation could also be considered at the same time to fulfill the objective of inventory control.

Lastly, by using customer characteristics to segment customers, retailer can optimally target and reach the segments. Specifically, the model can be used to assess the optimal level of markdown at the segment-level. This provides the critical insights for retailers to assess the profit impact of various markdown and promotion scenarios, at both aggregate and segment level. As a result, retailers can optimize their profit by targeting profitable segments and reduce offering markdown and promotion to low profitable consumers.

3.6.3 Limitation and Future Research

This study has a few limitations that can be addressed in future research. Firstly, this study focused only on demographic and behavioral variables for segments. The variable selection procedures, especially for the consumer-level covariates are largely considerate based on availability of data. However, this study primarily focused on proposing an empirical procedure for optimal markdown based on profitability model, rather than the variable selection problems. The variables for segmentation should vary based on industries and objectives, and availability of data. Theoretically, it can be demographic-based, behavioral-based, product-spaced (e.g., assortment), psychological-based (e.g., attitude, intention), geographical-based, lifestyle-based, and even emerging social-based segmentation. Incorporating more segmentation variables could improve the targetability of segmentation-scheme, but the rationale of profit maximization remains consistent. Secondly, we did not distinguish types of markdown pricing mechanism. In practice, markdown can be framed via various forms including a direct percentage discount, absolute dollars off on the total bill or issuing voucher. Earlier studies have investigated the effect of pricing promotion framing on price expectation and choices (DelVecchio et al. 2007). Such framing effect of promotion has been neglected in this study; and future investigation to distinguish the effects is an interesting research direction. For example, what are the optimal markdowns in terms of percentage for direct discount and dollars off as markdown should be set for different types of markdown for profit maximization. Finally, this study measured the customer profitability in terms of absolute contribution margin. Earlier studies used various customer profitability models to measure the profitability at both aggregate and individual levels (e.g., (Bowman and Narayandas 2004)).

REFERENCE

AC Nielson. 2013. "A Mobile Shopper's Journey: From the Couch to the Store (and Back Again)." from http://www.nielsen.com/us/en/insights/news/2013/a-mobile-shoppers-journey--from-the-couch-to-the-store--and-back.html

Ailawadi, K.L., Beauchamp, J., Donthu, N., Gauri, D.K., and Shankar, V. 2009. "Communication and Promotion Decisions in Retailing: A Review and Directions for Future Research," *Journal of Retailing* (85:1), pp. 42-55.

Allenby, G.M., and Rossi, P.E. 1998. "Marketing Models of Consumer Heterogeneity," *Journal of Econometrics* (89:1), pp. 57-78.

Andrews, R.L., and Currim, I.S. 2002. "Identifying Segments with Identical Choice Behaviors across Product Categories: An Intercategory Logit Mixture Model," *International Journal of Research in Marketing* (19:1), pp. 65-79.

Andrews, R.L., and Currim, I.S. 2003. "A Comparison of Segment Retention Criteria for Finite Mixture Logit Models," *Journal of Marketing Research* (40:2), pp. 235-243.

Aviv, Y., and Pazgal, A. 2008. "Optimal Pricing of Seasonal Products in the Presence of Forward-Looking Consumers," *Manufacturing & Service Operations Management* (10:3), pp. 339-359.

Bakos, J.Y. 1997. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science* (43:12), pp. 1676-1692.

Bandyopadhyay, S., Barron, J.M., and Chaturvedi, A.R. 2005. "Competition among Sellers in Online Exchanges," *Information Systems Research* (16:1), pp. 47-60.

Bapna, R., Goes, P., Wei, K.K., and Zhang, Z. 2011. "A Finite Mixture Logit Model to Segment and Predict Electronic Payments System Adoption," *Information Systems Research* (22:1), pp. 118-133.

Barua, A., Kriebel, C.H., and Mukhopadhyay, T. 1991. "An Economic Analysis of Strategic Information Technology Investments," *MIS quarterly* (15:3), pp. 313-331.

Baudry, J.-P., Raftery, A.E., Celeux, G., Lo, K., and Gottardo, R. 2010. "Combining Mixture Components for Clustering," *Journal of Computational and Graphical Statistics* (19:2), pp. 332–353.

Baye, M.R., and Morgan, J. 2001. "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," *American Economic Review* (91:3), pp. 454-474.

Bayus, B.L., and Mehta, R. 1995. "A Segmentation Model for the Targeted Marketing of Consumer Durables," *Journal of Marketing Research* (32:4), pp. 463-469.

Besanko, D., Dubé, J.-P., and Gupta, S. 2003. "Competitive Price Discrimination Strategies in a Vertical Channel Using Aggregate Retail Data," *Management Science* (49:9), pp. 1121-1138.

Bitran, G.R., and Mondschein, S.V. 1997. "Periodic Pricing of Seasonal Products in Retailing," *Management Science* (43:1), pp. 64-79.

Blattberg, R.C., Kim, B.-D., and Neslin, S.A. 2008. *Why Database Marketing?* Springer New York.

Bolton, R.N., Kannan, P.K., and Bramlett, M.D. 2000. "Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value," *Journal of the academy of marketing science* (28:1), pp. 95-108.

Bowman, D., and Narayandas, D. 2004. "Linking Customer Management Effort to Customer Profitability in Business Markets," *Journal of Marketing Research* (41:4), pp. 433-447.

Brynjolfsson, E. 1996. "The Contribution of Information Technology to Consumer Welfare," *Information Systems Research* (7:3), pp. 281-300.

Bucklin, R.E., and Gupta, S. 1992. "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach," *Journal of Marketing Research* (29:2), pp. 201-215.

Bucklin, R.E., Gupta, S., and Siddarth, S. 1998. "Determining Segmentation in Sales Response across Consumer Purchase Behaviors," *Journal of Marketing Research* (35:2), pp. 189-197.

Chen, Y., and Iyer, G. 2002. "Research Note Consumer Addressability and Customized Pricing," *Marketing Science* (21:2), pp. 197-208.

Chen, Y., Iyer, G., and Padmanabhan, V. 2002. "Referral Infomediaries," *Marketing Science* (21:4), pp. 412-434.

Chen, Y., and Zhang, Z.J. 2009. "Dynamic Targeted Pricing with Strategic Consumers," *International Journal of Industrial Organization* (27:1), pp. 43-50.

Chintagunta, P.K. 2002. "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research* (39:2), pp. 141-154.

Cool, K., and Schendel, D. 1988. "Performance Differences among Strategic Group Members," *Strategic Management Journal* (9:3), pp. 207-223.

Crawford, G.S., and Shum, M. 2005. "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica* (73:4), pp. 1137-1173.

DelVecchio, D., Krishnan, H.S., and Smith, D.C. 2007. "Cents or Percent? The Effects of Promotion Framing on Price Expectations and Choice," *Journal of Marketing* (71:3), pp. 158-170.

Demirhan, D., Jacob, V.S., and Raghunathan, S. 2006. "Information Technology Investment Strategies under Declining Technology Cost," *Journal of Management Information Systems* (22:3), pp. 321-350.

DeSarbo, W.S., Grewal, R., and Scott, C.J. 2008. "A Clusterwise Bilinear Multidimensional Scaling Methodology for Simultaneous Segmentation and Positioning Analyses," *Journal of Marketing Research* (45:3), pp. 280-292.

Desarbo, W.S., Jedidi, K., and Sinha, I. 2001. "Customer Value Analysis in a Heterogeneous Market," *Strategic Management Journal* (22:9), pp. 845-857.

Dziak, J.J., Coffman, D.L., Lanza, S.T., and Li, R. 2012. "Sensitivity and Specificity of Information Criteria," The Methodology Center and Department of Statistics, Penn State, The Pennsylvania State University.

Eckstein, Z., and Wolpin, K.I. 1990. "Estimating a Market Equilibrium Search Model from Panel Data on Individuals," *Econometrica: Journal of the Econometric Society* (58:4), pp. 783-808.

Eliashberg, J., and Steinberg, R. 1993. "Marketing-Production Joint Decision-Making," *Handbooks in Operations Research and Management Science* (5), pp. 827-880.

Elmaghraby, W., and Keskinocak, P. 2003. "Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions," *Management Science* (49:10), pp. 1287-1309.

Forrester Research. 2013. "The State of Loyalty Programs 2013."

Gerstner, E., and Hess, J.D. 1991. "A Theory of Channel Price Promotions," *The American Economic Review* (81:4), pp. 872-886.

Ghose, A., Mukhopadhyay, T., and Rajan, U. 2007. "The Impact of Internet Referral Services on a Supply Chain," *Information Systems Research* (18:3), pp. 300-319.

Ghose, A., and Yao, Y. 2011. "Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets," *Information Systems Research* (22:2), pp. 269-288.

Gowrisankaran, G., Mitchell, M.F., and Moro, A. 2008. "Electoral Design and Voter Welfare from the Us Senate: Evidence from a Dynamic Selection Model," *Review of Economic Dynamics* (11:1), pp. 1-17.

Grewal, D., Ailawadi, K.L., Gauri, D., Hall, K., Kopalle, P., and Robertson, J.R. 2011. "Innovations in Retail Pricing and Promotions," *Journal of Retailing* (87), pp. S43-S52.

Gupta, D., Hill, A.V., and Bouzdine-Chameeva, T. 2006. "A Pricing Model for Clearing End-of-Season Retail Inventory," *European Journal of Operational Research* (170:2), pp. 518-540.

Gupta, S., and Chintagunta, P.K. 1994. "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models," *Journal of Marketing Research* (31:1), pp. 128-136.

Hanssens, D.M., and Parsons, L.J. 1993. "Econometric and Time-Series Market Response Models," *Handbooks in Operations Research and Management Science* (5), pp. 409-464.

Heching, A., Gallego, G., and van Ryzin, G. 2002. "Mark-Down Pricing: An Empirical Analysis of Policies and Revenue Potential at One Apparel Retailer," *Journal of Revenue and Pricing Management* (1:2), pp. 139-160.

Hendel, I., and Nevo, A. 2013. "Intertemporal Price Discrimination in Storable Goods Markets," *American Economic Review* (103:7), pp. 2722-2751.

Hendricks, K.B., Singhal, V.R., and Stratman, J.K. 2007. "The Impact of Enterprise Systems on Corporate Performance: A Study of Erp, Scm, and Crm System Implementations," *Journal of Operations Management* (25:1), pp. 65-82.

Hitt, L.M., and Brynjolfsson, E. 1996. "Productivity, Business Profitability, and Consumer Surplus: Three Different Measures of Information Technology Value," *MIS quarterly* (20:2), pp. 121-142.

Huang, J., Leng, M., and Parlar, M. 2013. "Demand Functions in Decision Modeling: A Comprehensive Survey and Research Directions," *Decision Sciences* (44:3), pp. 557-609.

Hughes, A.M. 2006. *Strategic Database Marketing*. McGraw-Hill New York.

Iyer, G., and Pazgal, A. 2003. "Internet Shopping Agents: Virtual Co-Location and Competition," *Marketing Science* (22:1), pp. 85-106.

Iyer, G., Soberman, D., and Villas-Boas, J.M. 2005. "The Targeting of Advertising," *Marketing Science* (24:3), pp. 461-476.

Jayachandran, S., Sharma, S., Kaufman, P., and Raman, P. 2005. "The Role of Relational Information Processes and Technology Use in Customer Relationship Management," *Journal of Marketing* (69:4), pp. 177-192.

Jedidi, K., Jagpal, H.S., and DeSarbo, W.S. 1997. "Finite-Mixture Structural Equation Models for Response-Based Segmentation and Unobserved Heterogeneity," *Marketing Science* (16:1), pp. 39-59.

Jeuland, A.P., and Shugan, S.M. 1988. "Note—Channel of Distribution Profits When Channel Members Form Conjectures," *Marketing Science* (7:2), pp. 202-210.

Jing, B., and Wen, Z. 2008. "Finitely Loyal Customers, Switchers, and Equilibrium Price Promotion," *Journal of Economics and Management Strategy* (17:3), pp. 683-707.

Kamakura, W.A., Kim, B.-D., and Lee, J. 1996. "Modeling Preference and Structural Heterogeneity in Consumer Choice," *Marketing Science* (15:2), pp. 152-172.

Kamakura, W.A., and Russell, G. 1989. "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research* (26:4), pp. 379-390.

Keane, M.P., and Wolpin, K.I. 1997. "The Career Decisions of Young Men," *Journal of political Economy* (105:3), pp. 473-522.

Kotler, P., and Keller, K. 2011. *Marketing Management*, (14 ed.). Pearson Education Canada.

Levy, M., Grewal, D., Kopalle, P.K., and Hess, J.D. 2004. "Emerging Trends in Retail Pricing Practice: Implications for Research," *Journal of Retailing* (80:3), pp. xiii-xxi.

Lewis, M. 2004. "The Influence of Loyalty Programs and Short-Term Promotions on Customer Retention," *Journal of Marketing Research* (41:3), pp. 281-292.

Lin, T.H., and Dayton, C.M. 1997. "Model Selection Information Criteria for Non-Nested Latent Class Models," *Journal of Educational and Behavioral Statistics* (22:3), pp. 249-264.

Loyalty360. 2013. "Customers Want Online Shopping Options." from http://loyalty360.org/resources/article/customers-want-online-shopping-options

MarketWatch. 2012. "5 Top Price-Compare Apps." from http://www.marketwatch.com/story/5-of-the-best-price-comparison-apps-1332470811226

McKinsey. 2012. "Loyalty: Is It Really Working for You?."

McLachlan, G., and Peel, D. 2004. *Finite Mixture Models*. John Wiley & Sons.

Mithas, S., Krishnan, M.S., and Fornell, C. 2005. "Why Do Customer Relationship Management Applications Affect Customer Satisfaction?," *Journal of Marketing* (69:4), pp. 201-209.

Mobile Marketing Association. 2011. "Mobile Location Based Services Marketing Whitepaper," Mobile Marketing Association.

Naik, P.A., Shi, P., and Tsai, C.-L. 2007. "Extending the Akaike Information Criterion to Mixture Regression Models," *Journal of the American Statistical Association* (102:477), pp. 244-254.

Narasimhan, C. 1988. "Competitive Promotional Strategies," *Journal of Business* (61:4), pp. 427-449.

Nijs, V.R., Dekimpe, M.G., Steenkamps, J.-B.E., and Hanssens, D.M. 2001. "The Category-Demand Effects of Price Promotions," *Marketing science* (20:1), pp. 1-22.

Nylund, K.L., Asparouhov, T., and Muthén, B.O. 2007. "Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture

Modeling: A Monte Carlo Simulation Study," *Structural equation modeling* (14:4), pp. 535-569.

Pashigian, B.P. 1988. "Demand Uncertainty and Sales: A Study of Fashion and Markdown Pricing," *The American Economic Review* (78:5), pp. 936-953.

Pashigian, B.P., and Bowen, B. 1991. "Why Are Products Sold on Sale?: Explanations of Pricing Regularities," *The Quarterly Journal of Economics* (106:4), pp. 1015-1038.

Pauwels, K., Hanssens, D.M., and Siddarth, S. 2002. "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity," *Journal of marketing research* (39:4), pp. 421-439.

Payne, A., and Frow, P. 2005. "A Strategic Framework for Customer Relationship Management," *Journal of marketing* (69:4), pp. 167-176.

Raju, J.S., Srinivasan, V., and Lal, R. 1990. "The Effects of Brand Loyalty on Competitive Price Promotional Strategies," *Management Science* (36:3), pp. 276-304.

Rao, R.C. 1991. "Pricing and Promotions in Asymmetric Duopolies," *Marketing Science* (10:2), pp. 131-144.

Rao, V.R. 1984. "Pricing Research in Marketing: The State of the Art," *Journal of Business* (57:1), pp. S39-S60.

Rao, V.R. 1993. "Pricing Models in Marketing," *Handbooks in Operations Research and Management Science* (5), pp. 517-552.

Reinartz, W., and Kumar, V. 2006. "Customer Relationship Management: A Databased Approach." New Jersey: John Wiley and Sons.

Reinartz, W., Thomas, J.S., and Bascoul, G. 2008. "Investigating Cross‐Buying and Customer Loyalty," *Journal of Interactive Marketing* (22:1), pp. 5-20.

Reutterer, T., Mild, A., Natter, M., and Taudes, A. 2006. "A Dynamic Segmentation Approach for Targeting and Customizing Direct Marketing Campaigns," *Journal of Interactive Marketing* (20:3‐4), pp. 43-57.

Rindfleisch, A., and Heide, J.B. 1997. "Transaction Cost Analysis: Past, Present, and Future Applications," *Journal of Marketing* (61:4), pp. 30-54.

Rust, R.T., and Chung, T.S. 2006. "Marketing Models of Service and Relationships," *Marketing Science* (25:6), pp. 560-580.

Rust, R.T., and Verhoef, P.C. 2005. "Optimizing the Marketing Interventions Mix in Intermediate-Term Crm," *Marketing Science* (24:3), pp. 477-489.

Ryals, L. 2005. "Making Customer Relationship Management Work: The Measurement and Profitable Management of Customer Relationships," *Journal of Marketing* (69:4), pp. 252-261.

Salop, S., and Stiglitz, J. 1977. "Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion," *The Review of Economic Studies* (44:3), pp. 493-510.

Shankar, V., and Bolton, R.N. 2004. "An Empirical Analysis of Determinants of Retailer Pricing Strategy," *Marketing Science* (23:1), pp. 28-49.

Shapiro, B.P., Rangan, V.K., Moriarty, R.T., and Ross, E.B. 1987. "Manage Customers for Profits (Not Just Sales)," *Harvard Business Review* (65:5), pp. 101-108.

Song, Y., Ray, S., and Li, S. 2008. "Structural Properties of Buyback Contracts for Price-Setting Newsvendors," *Manufacturing & Service Operations Management* (10:1), pp. 1-18.

Soysal, G.P., and Krishnamurthi, L. 2012. "Demand Dynamics in the Seasonal Goods Industry: An Empirical Analysis," *Marketing Science* (31:2), pp. 293-316.

Srinivasan, R., and Moorman, C. 2005. "Strategic Firm Commitments and Rewards for Customer Relationship Management in Online Retailing," *Journal of Marketing* (69:4), pp. 193-200.

Strategy Analytics. 2011. "The 10 Billion Rule: Location, Location, Location," Strategy Analytics.

Su, X. 2007. "Intertemporal Pricing with Strategic Customer Behavior," *Management Science* (53:5), pp. 726-741.

Sun, B. 2006. "Invited Commentary-Technology Innovation and Implications for Customer Relationship Management," *Marketing Science* (25:6), pp. 594-597.

Sweeting, A. 2012. "Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets," *Journal of Political Economy* (120:6), pp. 1133-1172.

Thatcher, M.E., and Pingry, D.E. 2004. "An Economic Model of Product Quality and It Value," *Information Systems Research* (15:3), pp. 268-286.

Tuma, M., and Decker, R. 2013. "Finite Mixture Models in Market Segmentation: A Review and Suggestions for Best Practices," *Electronic Journal of Business Research Methods* (11:1).

USA TODAY. 2012. " Shopkick 3.0 Rewards Home Shoppers:Get 'Kicks' with Picks before Hitting Stores."

Varian, H.R. 1980. "A Model of Sales," *The American Economic Review* (70:4), pp. 651-659.

Verhoef, P.C. 2003. "Understanding the Effect of Customer Relationship Management Efforts on Customer Retention and Customer Share Development," *Journal of marketing* (67:4), pp. 30-45.

Verhoef, P.C., Spring, P.N., Hoekstra, J.C., and Leeflang, P.S. 2003. "The Commercial Use of Segmentation and Predictive Modeling Techniques for Database Marketing in the Netherlands," *Decision Support Systems* (34:4), pp. 471-481.

Vermunt, J.K., and Magidson, J. 2005. "Technical Guide for Latent Gold 4.0: Basic and Advanced." Belmont (Mass.): Statistical Innovations Inc.

Warner, E.J., and Barsky, R.B. 1995. "The Timing and Magnitude of Retail Store Markdowns: Evidence from Weekends and Holidays," *The Quarterly Journal of Economics* (110:2), pp. 321-352.

Washington Post. 2011. " Put Down Those Coupon Clippers."

Weber, T.A., and Zheng, Z.E. 2007. "A Model of Search Intermediaries and Paid Referrals," *Information Systems Research* (18:4), pp. 414-436.

Wedel, M., and Kamakura, W. 2000. *Market Segmentation: Conceptual and Methodological Foundations*, (2 ed.). Boston: Kluwer Academic Publishers.

Xu, L., Chen, J., and Whinston, A. 2010. "Oligopolistic Pricing with Online Search," *Journal of Management information systems* (27:3), pp. 111-142.

Zablah, A.R., Bellenger, D.N., Straub, D.W., and Johnston, W.J. 2012. "Performance Implications of Crm Technology Use: A Multilevel Field Study of Business Customers and Their Providers in the Telecommunications Industry," *Information Systems Research* (23:2), pp. 418-435.

APPENDIX A: Proof of Chapter 2

Proof of Lemma 1

In this subgame, similar to the proofs of proposition 2-5 in (Narasimhan 1988), we have that in this mixed-strategy equilibrium: 1) The price support for store price is continuous. 2) Neither form can have a probability mass point below 1 in its support. Since D_L and p_i^c are exogenously given, we directly apply the results from Narasimhan (1988) or Varian (1980) and get the results accordingly. ■

Proof of Lemma 2

In this subgame, firms are essentially in Bertrand competition for the consumers who use LBS infomediary. As a result, the equilibrium price and profit would be zero for these consumers. For the rest of the $(1-k)D_L$ consumers, $(1-k)\alpha D_L$ of them would buy from L_1 or L_2, and $(1-k)D_{L\beta}$ consumers would buy from the retailer offering lower price. Thus the competition is equivalent to Lemma 1 with a shrunk market. As a result, $1-\frac{\alpha(p_i^c-p)}{\beta p}$ and $(1-k)\alpha D_L p_i^c$ are equilibrium price distribution and associated profit. ■

Proof of Lemma 3

The derivation follows directly from (Chen et al. 2002). First, the price support for Retailer 1 and Retailer 2 are continuous with $(p_{L1}^b, p_{L1}^m)\cup(p_{L1}^m, p_{L1}^c)$ and

$(p_{L2}^b, p_{L2}^m) \cup (p_{L2}^m, p_{L2}^c)$ respectively. Second, Retailer 1's profit is the sum of two expected profits from two price intervals in two channels; whereas Retailer 2's has two mixed-strategies pricing in a single channel. In our model, we have

$$\begin{aligned}
\pi_{L1} &= (1-k)D_{L1}p_{L1} + (1-k)D_{L\beta}(1-F_{L2}(p_{L1}))p_{L1} \\
&\quad + kD_{L1}p_{L1}^{LBS} + k(D_{L2}+D_{L\beta})(1-F_{L2}(p_{L1}^{LBS}))p_{L1}^{LBS} \\
\pi_{L2} &= (1-k)D_{L2}p_{L2} + (1-k)D_{L\beta}(1-F_{L1}(p_{L2}))p_{L2} \\
&\quad + k(D_{L2}+D_{L\beta})(1-F_{L1}^{LBS}(p_{L2}))p_{L2}.
\end{aligned}$$

Following Proposition 1 and 2 of (Chen et al. (2002)), with the exogenously given D_{L1}, D_{L2}, D_L and price cap p_i^c, we can derive the equilibrium profit and price distribution as shown in Lemma 3. ■

Proof of Proposition 1

By substituting eq. (8) into Lemma 1, we have.

$$\begin{aligned}
\pi_{L1} &= \alpha\left(\frac{1}{2} + \frac{3(p_{R1}^c - p_{L1}^c + p_{R2}^c - p_{L2}^c)}{4t}\right)p_{L1}^c \\
\pi_{R1} &= \alpha\left(\frac{1}{2} - \frac{3(p_{R1}^c - p_{L1}^c + p_{R2}^c - p_{L2}^c)}{4t}\right)p_{R1}^c \\
\pi_{L2} &= \alpha\left(\frac{1}{2} + \frac{3(p_{R1}^c - p_{L1}^c + p_{R2}^c - p_{L2}^c)}{4t}\right)p_{L2}^c \\
\pi_{R2} &= \alpha\left(\frac{1}{2} - \frac{3(p_{R1}^c - p_{L1}^c + p_{R2}^c - p_{L2}^c)}{4t}\right)p_{R2}^c
\end{aligned}$$

Take First-Order-Condition and solve for four posted prices

$$\begin{aligned}
p_i^c &= \frac{2}{3}t, \\
\pi_i &= \frac{t\alpha}{3}.
\end{aligned}$$

By symmetric setting, all stores should get same price and profit. ■

Proof of Proposition 2

Substitute eq. (8) into Lemma 2. Following the same procedure that is used in proof of Proposition 1, we can solve for Proposition 2. By symmetric setting, all stores should get same price and profit. ■

Proof of Proposition 3

Substitute eq. (8) into Lemma 3. Following the same procedure that is used in proof of Proposition 1 and 2 we can solve for Proposition 2. By symmetric setting, all stores should get same price and profit. ■

Proof of Proposition 4

We draw a simple payoff matrix as follow. A, B, C, D represents the profit in Proposition 1, 2, and 3.

Table 9 Payoff Matrix for LBS Adoption

		Retailer 2	
		Adopt	**Not Adopt**
Retailer 1	**Adopt**	A, A	C, D
	Not Adopt	D, C	B, B

To identify the Nash Equilibrium from the payoff matrix in Table 6, essentially we need to compare B and C, then A and D.

First, we show C is less then B,

$$\begin{aligned}
&C-B\\
&=t\alpha^2(1-k)\frac{((1-\alpha)^2+k\alpha)^2}{(k(3\alpha-1)(2-\alpha)+2(1-\alpha)^2)((1-\alpha)^2-(1-2\alpha)k)}-\frac{t\alpha}{3}\\
&=\frac{1}{3}t\alpha\frac{(3\alpha^3)k^3+(\alpha-2)(2\alpha-1)(-3\alpha+3\alpha^2+1)k^2+(14\alpha-15\alpha^2+3\alpha^3-4)(1-\alpha)^2k+(2-3\alpha)(1-\alpha)^4}{-(k(3\alpha-1)(2-\alpha)+2(1-\alpha)^2)((1-\alpha)^2-(1-2\alpha)k)}
\end{aligned}$$

The sign of the expression depends on the numerator.

Since we know *k<1-α*,

$$\begin{aligned}
&(3\alpha^3)k^3+(\alpha-2)(2\alpha-1)(-3\alpha+3\alpha^2+1)k^2+(14\alpha-15\alpha^2+3\alpha^3-4)(1-\alpha)^2k+(2-3\alpha)(1-\alpha)^4\\
&>(3\alpha^3)k^3+(\alpha-2)(2\alpha-1)(-3\alpha+3\alpha^2+1)k^2+(14\alpha-15\alpha^2+3\alpha^3-4)(1-\alpha)^2k+(2-3\alpha)(1-\alpha)^3\\
&=k(3\alpha^3k^2+(6\alpha^4-21\alpha^3+23\alpha^2-11\alpha+2)k+(9\alpha-12\alpha^2+3\alpha^3-2)(1-\alpha)^2)\\
&>k(3\alpha^3k^2+(6\alpha^4-21\alpha^3+23\alpha^2-11\alpha+2)k+(9\alpha-12\alpha^2+3\alpha^3-2)(1-\alpha)k)\\
&=k^2\alpha^2(2-(1-k)3\alpha+3\alpha^2-3\alpha)\\
&>k^2\alpha^2(2-3\alpha^2+3\alpha^2-3\alpha)\\
&=k^2\alpha^2(2-3\alpha)\\
&>0
\end{aligned}$$

As a result, we have shown C<B.

Second, we compare A and D.

$$\begin{aligned}
&D-A\\
&=\frac{1}{3}\alpha t(1-\alpha)^3\frac{1-k}{((1-\alpha)^2-(1-2\alpha)k)}-\frac{t\alpha}{3}(1-k)\\
&=\frac{1}{3}t\alpha(1-k)\frac{(1-2\alpha)k-\alpha(1-\alpha)^2}{(1-\alpha)^2-(1-2\alpha)k}.
\end{aligned}$$

The sign depends on $(1-2\alpha)k-\alpha(1-\alpha)^2$. As a result, if $k>\dfrac{\alpha(1-\alpha)^2}{(1-2\alpha)}$,

$(1-2\alpha)k-\alpha(1-\alpha)^2>0$ and there is one pure strategy Nash equilibrium is

"Neither Adopt", otherwise there are two pure strategy Nash equilibria for "Both adopt" and "Neither adopt", and a mixed strategy between the two.

However, we also assume $k < 1-\alpha$, therefore $1-\alpha = \frac{\alpha(1-\alpha)^2}{1-2\alpha} \Rightarrow \alpha = \frac{1}{3}$. Thus the equilibrium is summarized as follows:

1. If $\alpha \geq \frac{1}{3}, k < 1-\alpha \leq \frac{\alpha(1-\alpha)^2}{1-2\alpha}$ there are two pure strategy Nash equilibria (A, A) and (B, B), and a mixed strategy between the two.

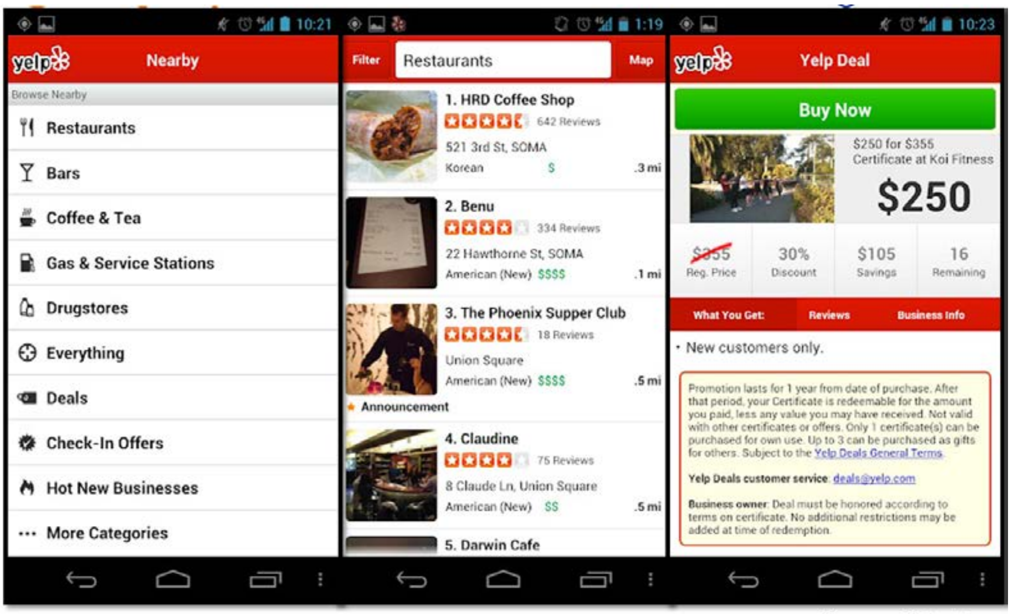
2. If $\alpha < \frac{1}{3}$, $\frac{\alpha(1-\alpha)^2}{1-2\alpha} < 1-\alpha$,

(a) If $k < \frac{\alpha(1-\alpha)^2}{1-2\alpha}$, there are two pure strategy Nash equilibria (A, A) and (B, B), and a mixed strategy between the two.

(b) If $\frac{\alpha(1-\alpha)^2}{1-2\alpha} < k < 1-\alpha$, there is one pure strategy Nash equilibrium (B, B).

■

APPENDIX B: An LBS Application Example



Source: Yelp App

Figure 10 Example of LBS App as Infomediary

APPENDIX C: Sample of Price & Promotion FKB

Table 10 Examples of FKB's Markdown and Promotion

Types	Example
Price Markdown	End of Season Sales: 20% off Chrisms Sales: 15% off
CRM-based Rebate	double points reward
Voucher	$10 voucher with min $100
Events	Kids Fashion Show, Store Opening Ceremony, Brand Anniversary Sales
Freebie	Free Toy, watch, bag with min $100
Bank specific promotion	20% for AMEX card holder, 10% for Citibank Card holder
Luck Draw	1 Chance to win a smartphone

APPENDIX D: Descriptive Statistics of Product Category

Table 11 Product and Cost of Product Category

Product Category	Mean Posted Price	Mean Unit Cost
BABY BOY SHORTS	**26.89**	**7.02**
BABY BOY TEE	**16.71**	**3.36**
• L/S TEE	19.16	3.85
• S/S TEE	16.41	3.32
BABY GIRL DRESS	**30.68**	**7.08**
BABY GIRL PANTS	**22.25**	**4.93**
• C PANTS	21.08	4.63
• L PANTS	23.71	5.29
BABY GIRL TEE	**17.12**	**3.55**
• L/S TEE	18.87	3.69
• S/S TEE	16.92	3.49
KIDS BOY SHORTS	**34.99**	**9.05**
KIDS BOY TEE	**19.34**	**4.35**
• L/S TEE	23.97	5.31
• S/S TEE	19.13	4.30
KIDS GIRL DRESS	**41.20**	**9.82**
KIDS GIRL PANTS	**29.65**	**7.16**
• C PANTS	26.47	6.14
• L PANTS	37.41	9.66
KIDS GIRL TEE	**20.06**	**4.55**
• L/S TEE	23.10	5.08
• S/S TEE	20.03	4.51

APPENDIX E: Technical Details of Model Selection

Researchers have used information criteria such as Akaike information criterion (AIC) (Kamakura and Russell 1989), Bayesian information criterion (BIC) (Bucklin and Gupta 1992; Gupta and Chintagunta 1994; Kamakura et al. 1996), Consistent AIC (CAIC, penalize model with more parameters and higher number of segments) and AIC3 (Andrews and Currim 2003) to determine the optima number of segments (Wedel and Kamakura 2000) for the data sample. Generally, the model with lowest information criteria should be selected.

However, no general consensus has been achieved on the universal best criteria to use. Instead it usually depends on the nature of research question and data. Numerous studies in marketing, economics and statistics are trying to evaluate the model selection criteria using simulations. For example, when a very simple model was used as the true model, BIC and CAIC were more likely to choose the true model than AIC, which tended to choose an unnecessarily complicated one (Lin and Dayton 1997). Dziak et al. (2012) suggested that, in most of the scenarios (especially when sample size is large), BIC and CAIC almost always selected the correct model size, while AIC had a much smaller accuracy in these scenarios because of a tendency to over-fit the data. Generally speaking, BIC provide more parsimony in most cases and generally perform well (Baudry et al. 2010; Tuma and Decker 2013). Nylund et al. (2007) presented various simulations on the performance of various information criterion and tests for selecting the number of classes in finite mixture model, in which BIC performed much better than AIC (which tended to over-fit) or

CAIC (which tended to under-fit). As a result, this study mostly replies on BIC for model selection but we also report various goodness-of-fit measures for comparison.

Quality of classification is also used to evaluate the model of finite mixture estimation. Particularly, when the information criterion is satisfactory, it is also suggested to use an entropy-based measure to investigate the degree of certainty/separation in classification (Desarbo et al. 2001; Jedidi et al. 1997; Wedel and Kamakura 2000), specified as follows:

$$E_s = 1 + \frac{\sum_{i=1}^{N} \sum_{s}^{S} P_{is} \cdot \ln(P_{is})}{N \ln(S)}$$

In this case, we report the entropy-based measure, which is between 0 and 1 in the analysis. A value close to 0 indicates that the posterior probabilities are not well separated. In this case, the posterior segmentation probabilities show that every individual consumer belongs to every segment with equal probabilities. A value chose to 1 suggests a discrete partitioning of the sample. In other words, every consumer belongs to one of the segment with probability 1.

APPENDIX F: Model Selection for Demand and Profit Model

Table 12 Model Selection for Demand Model

		Information Criteria					
S	**LL**	**AIC**	**BIC**	**AIC3**	**CAIC**	**Entropy Measure**	**Pseudo-R^2**
1	-101309.24	202756.49	203249.93	202825.49	203318.93	N.A.	0.11
2	-100929.96s	202159.93	**203232.63**	**202159.93**	**202159.93**	0.59	0.15
3	-100763.49	201988.97	203640.93	202219.97	203871.93	0.59	0.17
4	-100649.26	**201922.52**	204153.74	202234.52	204465.74	0.62	0.18

Table 13 Model Selection for Profitability Model

			Information Criteria				
S	**LL**	**AIC**	**BIC**	**AIC3**	**CAIC**	**Entropy**	**Pseudo-R^2**
1	-41396.97	82935.94	83428.96	83006.94	83499.96	N.A.	0.53
2	-37197.30	74702.59	75771.97	74859.59	75925.97	0.63	0.57
3	-31239.72	62953.44	64599.18	63190.44	64836.18	0.70	0.58
4	-30226.46	61092.92	**63315.01**	61412.92	**63635.01**	**0.71**	**0.59**
5	-29873.91	60553.82	63352.27	60956.82	63755.27	0.63	0.57