Essays on Brand Alliance in Marketing

Submitted to the David A Tepper School of Business
in partial fulfillment for the requirements for the degree of
DOCTOR OF PHILOSOPHY
in Business Administration (Marketing)

By

Kevin YC Chung
Tepper School of Business
Carnegie Mellon University
5000 Forbes Avenue
Pittsburgh, PA 15213

Dissertation Committee:
Kannan Srinivasan (Chair)
Peter Boatwright
Joachim Vosgerau
Ramayya Krishnan

May 2013

Acknowledgments

I would like to thank my advsior Kannan Srinivasan for all his support and guidance for the past five years. I thank him for his encouragements and support on the works that I have pursued, which ultimately became part of this dissertation. I always enjoyed my conservation with him and greatly benefited from his candid advice, both in academic and in life.

I would also like to thank my committee members, Peter Boatwright, Joachim Vosgerau and Ramayya Krishnan. I thank them for taking their time to give feedback on my research.

Outside of the Carnegie Mellon University's community, I am especially thankful to Nitin Mehta and Wesley Hartmann for taking their valuable time to question and comment on my research and provide guidance. I greatly benefited from my conversations with them.

I would like to thank LARC (Living Analytics Research Center) and everyone involved. Many have worked hard to get the data that is now part of this dissertation. I especially thank Rob Kauffman, Rae Chang from Singapore Management University and Steve Fienberg and Ramayya Krishnan from Carnegie Mellon University.

I thank my parents and grandparents for helping me be where I am today. Without their love and support, I would not be where I am today.

Last and most importantly, I would like to thank my wife Andrea for all she has done. She is a constant source of joy in my life and I am blessed to have her as my companion.

Abstract

My dissertation aims to understand marketing activities that involve two or more disparate entities with linked association, resulting in joint promotion and branding. I investigate two such types of activity, an alliance between a celebrity and a brand, and an alliance between credit card companies and merchants. Both attempts to measure and identify the impact the promotion has on the consumer's decision process.

In the first essay, we quantify the economic worth of celebrity endorsements by studying the sales of endorsed products. We do so with the use of two unique data sets consisting of monthly golf ball sales and endorsers' quality levels. Our identification of the causal effect of a celebrity on the endorsed product is grounded on the endorsers' random performance over time that captures the variation in sales of the product. We find that there are substantial celebrity endorsement effects. We determine that endorsements not only induce consumers to switch brands, but also have a primary demand effect.

In the second essay, using daily customer transaction and program cost data from 2009-2011, we study the effects on consumer behavior of a novel Merchant Network Rebate Program implemented by a multinational bank in Singapore. With the only restriction being that it prohibits aggregation of rebate amount across cards, the rebate is instant with the same benefits offered to all bank issued credit cards, supplementing the existing card level benefits. The analysis takes advantage of the unique features of the program and the richness of data to understand how consumers spontaneously frame the options they face and how this impacts the decision process in and out of the program participating merchants. This has large managerial implication of how to better design the program.

Publications

Portions of the work described in this dissertation has also appeared in:

- Chung K YC, Derdenger T P, Srinivasan K, Economic Value of Celebrity Endorsements: Tiger Woods' Impact on Sales of Nike Golf Balls, *Marketing Science* March/April 2013 vol. 32 no. 2 271-293 .

Contents

List of Figures

Chapter 1

INTRODUCTION

Brand alliance is defined as a linked association in the form of either short or long term agreements that occur between brands, products or any distinctive proprietary assets.[1]Some examples include Coca Cola with Splenda brand to form "Diet Coke Sweetened with Splenda", United Airline partnering with the Chase Bank and offering "MilegePlus Explorer" credit card. If one considers a celebrity as possessing any proprietary assets, an endorsement would also qualify as an example of brand alliance in marketing.

Today, there are a plethora of marketing activities involving two or more disparate entities coming together jointly to promote and brand a product. My dissertation investigates two types of this brand alliance activity. Both attempt to measure and identify the impact that this type of promotion has on the consumer's decision process.

In Chapter 2, we look at an alliance between a celebrity and a brand. We quantify the economic worth of celebrity endorsements by studying the sales of endorsed products. We do so with the use of two unique data sets consisting of monthly golf ball sales and professional golfer (celebrity) quality levels. In particular, we examine the impact Tiger Woods had on sales of Nike golf balls. Our identification of the causal effect of a celebrity is grounded in the celebrity's random performance over time.

Using two different approaches, reduced form and structural, we find that there are substantial celebrity endorsement effects. From our structural model we determine that endorsements not only induce consumers to switch brands, a business stealing effect, but also have a primary demand effect. We determine from

2000-2010, the Nike golf ball division reaped an additional profit of $103 million through an acquisition of 9.9 million sales from Tiger Woods' endorsement effect. Moreover, having Tiger Woods endorse a brand leads to a price premium of roughly 2.5%. As a result, approximately 57% of Nike's investment of $181 million endorsement contract was recovered ***just*** in US golf ball sales alone.

In Chapter 3, we look at an alliance between credit card companies and merchants. In this work, we seek to establish a consumer's propensity to wait and accumulate rewards despite the fact that there is no financial "gain" in doing so. By examining consumer behavior from a network of rebate rewards programs from Singapore, the behavior of rewards-participating merchants are shown to vary considerably after the rebate program is introduced, even after one controls for variation due to merchants. The empirical analysis takes advantage of the variation of the time in which the rebates were rolled out across merchants as well as the variation of consumer shopping behavior in both the participating and non participating stores.

In contrast to the normative prescriptions of economic theory, we find evidence that consumers spontaneously frame the rebate in terms of "losses" as oppose to gains on the value function. We examine and demonstrate that consumers not only wait for the optimal time to redeem, where redemption coincides with larger percentage off than previous opportunities, but consumers also put significant effort in amassing rebates on a single card. In the program, consumers are unable to consolidate accrued rebates across cards. We thus investigate the extent to which consumers use a single card to amass rebates and the resultant effect on forgoing card-level benefits made available to them.

Chapter 2

Economic Value of Celebrity Endorsements: Tiger Woods' Impact on Sales of Nike Golf Balls

The general belief among marketing agencies is that the use of celebrity endorsements enhances product recall but not sales. David Ogilvy, the founder of Ogilvy & Mather, an international marketing agency is said to have preached that celebrity advertisements triggered above average product recall but resulted in below average sales. Similarly, Wilson's vice president of tennis division, Gene Buwick is said to have remarked that no company should expect an endorsement investment to come back in terms of added sales. Rather, the success of endorsement should be judged in terms of the visibility and exposure the celebrity would give to that company's product and the company itself.[2] On the other hand, there are examples that suggest celebrity endorsements actually lead to higher sales. For example, after Chanel signed Nicole Kidman in 2003, it is reported that global sales of Chanel's classic perfume jumped 30%.[3] Similarly, when Tiger Woods switched his endorsed ball from the Titleist brand to Nike in 2000, Nike's market share went from 0.9% to 4% in 6 months.

In this paper, we address the fundamental question of whether celebrity endorsements lead to higher sales and thus are a profitable marketing strategy to implement. This is especially pertinent question to answer today given that celebrity endorsements have become an essential component of many firms' promotional strategies. The importance is corroborated by the fact that in the past 30 years, there has been a surge in both the number and the size of the celebrity endorsement contracts. Despite the importance, few have attempted to quantify the economic worth of celebrity endorsers in product sales. One of the main difficulty arise from identifying the endorsement effect amongst many other confounding events that may give rise to the same outcome. Moreover, the impact of an endorsement is said to be contingent upon celebrity quality and credibility.[4] Due to this, those that have studied this domain have done so in an indirect manner–by using the event study methodology and looking at the fluctuation of stock prices during the time of the announcement of celebrity endorsements and thus omit the importance of quality and credibility in their analysis.[5][1] In this paper, in contrast to previous attempts, we answer the question by looking directly at the sales of the endorsed product and account for quality and credibility.

We have a unique golf data set that allows us to address our research questions. Studying celebrity endorsements in the context of the golf industry is fitting because golf has been the leading sports industry in the endorsement business. In "The Fortunate 50", a list of 50 top earning American athletes in salary, endorsement and appearance fees compiled by the Sports Illustrated, in 2008 and 2009, Tiger Woods and Phil Mickelson came 1st and 2nd respectively.[2] It is documented that Tiger Woods has consistently earned significantly more off the course than on the course by a variety of endorsers. In fact, it was believed in 2008 that Tiger Woods was on his way to become the first $1 billion athlete. In 2007, his earning from on course was $23 million while endorsement deals totaled $100 million.[3] [6] Structurally, the golf industry is a relatively insulated industry that has had a steady number of participants. It is estimated that over the past 10 years, the number of golfers remained steady at 26 to 30 million.[7]

We answer the fundamental question of whether celebrity endorsements lead to higher sales with the use of two empirical approaches, reduced form and structural. We first begin with a reduced form analysis to determine the impact on sales only. With this analysis, we use aggregate brand sales data to determine

[1]Specifically, Agrawal and Kamakura (1995) study 110 celebrity endorsement contracts and find that, on average, the market reacts positively on the announcement of celebrity endorsement contracts. Based on this result, they conclude that celebrity endorsements are viewed as a profitable advertising strategy. More recently, Knittel and Stango (2009) study the negative impact of Tiger Woods' scandal. By looking at the stock prices of the firms that Tiger Woods endorses, they estimate that, after the event in November 2009, shareholders of Tiger Woods' sponsors lost $5-12 billion relative to those firms that Woods did not endorse. Furthermore, they find that sports related sponsors suffered more than his other sponsors. To the best of our knowledge, these two papers are the closest in terms of what we are trying to study in our paper.

[2]http://sportsillustrated.cnn.com/more/specials/fortunate50/2009/index.html
http://sportsillustrated.cnn.com/more/specials/fortunate50/2008/index.html

[3]http://www.golfdigest.com/magazine/2008-02/gd50

the impact celebrities have with the use of a simple OLS estimator. What enables us to determine such an effect is the presence of endorser quality (world ranking) data and the fact that it randomly varies over time. Specifically, our identifying assumption is that as a celebrity's quality level decreases the endorsement effect he possesses decreases. Thus, the co-movement in exgoenous celebrity quality or performance and brand sales overtime allows us to identify a celebrity's causal effect on sales. Following our reduced form analysis, we move to a structural model of consumer demand and firm supply. In this analysis we employ the same identification strategy to answer more broadly the effects of celebrity endorsements. This structural model allows us to determine the impact on profit, price and market share of not only of the endorsed brand but its competitors as well.

By developing and estimating a structural demand model, we find that celebrity endorsements can create product differentiation and generate shifts in market share and thus should be thought of as a profitable marketing strategy. Furthermore, we empirically show that endorsements can have a strong effect on consumer utility such that endorsements have a dual component where existing customers switch to the more effective endorsed brand (business stealling) while bringing in additional sales from the outside (primary demand) which would have otherwise not occurred if it was not for the endorsement. Lastly, we find that firms were able to command a price premium when they sign high quality celebrities while competitors reacted to the endorsement by cutting price. After implementing several counterfactual scenarios we find, from 2000-2010, the Nike golf ball division reaped an additional profit of $103 million through an additional sale of 9.9 million dozen golf balls from Tiger Woods' endorsement effect. As a result, approximately 57% of Nike's investment on the golfer's endorsement was recovered just in US golf ball sales alone.

The paper is organized as follows: First, to motivate our empirical study, we provide a brief background on the celebrity endorsement and golf industry with a focus on the golf ball market in section 2.1 before providing an overview of the data with preliminary analysis in section 2.2. In section 2.3, we present some reduced form analysis and in section 2.4 we describe our structural empirical model. In section 2.5, empirical results are provided followed by the counterfactual in section 2.6. In section 2.7 we conclude with discussion on limitations with directions for future research.

2.1 Background Information

2.1.1 The Golf Industry

The golf industry in the United States generated direct revenues of $76 billion in 2005 up from $62 billion in 2000. At $76 billion, the golf industry is larger than the motion picture and the video industries. With the industry consisting of 7 main parts ranging from facility operations to real estate, golfer equipment/supplies and golf endorsements combined made up to be a $ 7.8 billion industry in 2005.[8] We present a general overview of the golf equipment used in the sport of golf. There are 3 main categories in golf equipment; bags, clubs and balls. Given that our paper assesses the impact of endorsement on sales of golf ball equipment, we include the overview of the other two categories in the appendix.

Golf Balls

Golf balls are estimated to generate $500 million dollars in annual sales.[9, 10] There are 1,051 models of golf balls that are listed on the United States Golf Association's list of conforming golf balls. It is believed by many experts in golf that the golf ball has more engineering per cubic centimeter than in any recreational product in the market.[11] Golf balls are usually white, weighing no more than 1.62 ounces with a diameter of no less than 1.68 inches.[12] In today's golf ball, there are three main components; the number of layers, the type of outer cover and the number of dimples.

Golf balls can have layers that ranges anywhere from two to five. Most golf balls for amateurs (least expensive) are two layered golf balls consisting only the outer cover material and a core. The core of a ball is the resilient rubber compound located in the center of a ball that provides the transfer of energy from the golf club to the ball at impact. Depending on the number of layers, two layered golf balls are often called the "two piece" ball, three layered a "three piece" and so on. In three piece golf balls, there is an extra layer of material between the core and the cover. This is usually a "mantle", which is a layer of polymer that are used both to control spin off of high speed impact and provide "feel". Four piece balls either have two mantles or two cores. There is only one five piece golf ball in the market today. The more layers a golf ball the higher cost of production and thus a higher retail price.

The type of outer cover on a golf ball determines how the golf ball “feels” under impact from the golf club. There are two main type of covers that are most widely used in the golf ball industry. The most popular is the ionomer/surlyn cover which is durable and resilient material made up of a blend of plastic resin. On the other hand, urethane is a softer and a more elastic material that is more expensive to manufacture. Urethane is about twice as thin as the surlyn cover and during the casting process it is known that urethane goes from a liquid to a solid in 30 seconds, leaving no room of error for the manufacturer. On the other hand, producing surlyn balls are known to be straightforward. It is said that in the time that 160 surlyn balls are produced, only 1 multilayer urethane cover ball can be produced. Most non premium golf balls are made of ionomer material while most premium golf balls that professional golfer use are made up of urethane cover.

Lastly, today’s golf balls are characterized by the dimples on the surface. These are small identically shaped indents that are usually circular. The main purpose of a dimple is that it creates the necessary aerodynamic forces for the ball to fly further and longer. Depending on the depth of the dimples, the trajectory of the flight differs, with shallow dimples creating higher flights while deeper dimples creating lower flights. Most golf balls today have 250-450 dimples. There have been differently shaped dimples to increase the number of coverage of the ball’s surface. It is understood that covering the golf ball with more dimples is generally more difficult to manufacture and are reflected in the retail price.

The characteristics of the golf ball is important in this paper as they are the inherent part of the product characteristics that differentiate the products. In estimation, these characteristics become valuable instruments for the endogenous price variable.

2.1.2 How Celebrity Endorsements Work in the Golf Industry

A celebrity endorsement is a relationship between a firm and a celebrity that occur for an agreed duration of time. In other words, while there is a matching that goes on between a celebrity and the firm, once an agreement is made and the contract is signed the relationship is binding for the agreed time period. However, when a firm is to select an endorser there are two important factors to consider: 1) the attractiveness of the celebrity-a more attractive/prominent endorser leads to a greater impact on sales and 2) the credibility of the celebrity-expertise and trustworthiness must be credible. The golf industry is a natural industry to study for two reasons. One, all celebrities (players) are ranked each week based upon their performance for the previous 104 weeks, which is a natural measure of celebrity attractiveness. And, since each celebrity plays with the equipment in weekly golf tournaments to earn prize money, this eliminates any issues of lack of player credibility.

Most celebrity endorsements in the golf industry are multi-year contract that are predetermined when contract agreements are signed with the contract specifying the celebrity's scope of services. These services include the product that will be physically used in tournaments during the endorsement periods (ball, club, apparel with logo, bag etc) and other services. For example, Tiger Woods signed a 5 year agreement deal with Nike golf for $100 million dollar with the condition that he will use Nike golf ball, clubs and apparel. The list of services are carefully considered and negotiated on both sides, the golfer's representative and the firm that wants to employ endorsements as part of their promotion strategy. The compensation arrangement will vary depending on the scope of services the firm impose on the celebrity as well as the visibility of the celebrity and his/her potential which dictates the size of compensation. For example, while Tiger Woods was able to command $20 million dollars per year from Nike, a typical PGA tour player that is ranked outside the top 50 earns anywhere from $100,000 to $500,000 per year from an endorsement deal. Contracts also often include a moral clause by the firm that prohibits certain behavior that may negatively impact it. In case of unforeseen circumstances, contracts often specify the rights of both parties for early termination from a multi-year endorsement contract.

2.1.3 Tiger Woods Endorsements

Tiger Woods' career began with endorsement deals with Nike Golf and Titleist brands in 1996. In the beginning, Tiger Woods endorsed Nike Golf apparel and shoes and Titleist golf balls and equipment. In 1996 Nike Golf was a new player in the golf industry and was only producing apparel and shoes. However, in 1999 Nike entered the golf equipment market where they would produce golf balls and clubs. In June of 2000 Tiger Woods was the the first players to switch from the Titleist golf ball to the Nike Golf ball. Such a switch cost Nike $100 million dollars and in return it secured a five year endorsement contract with Mr. Woods which included equipment, apparel and shoes. After the initial five year contract expired, Nike entered into another five year endorsement deal for yet another $100 million dollars. In total, for the decade of 2000 Nike paid

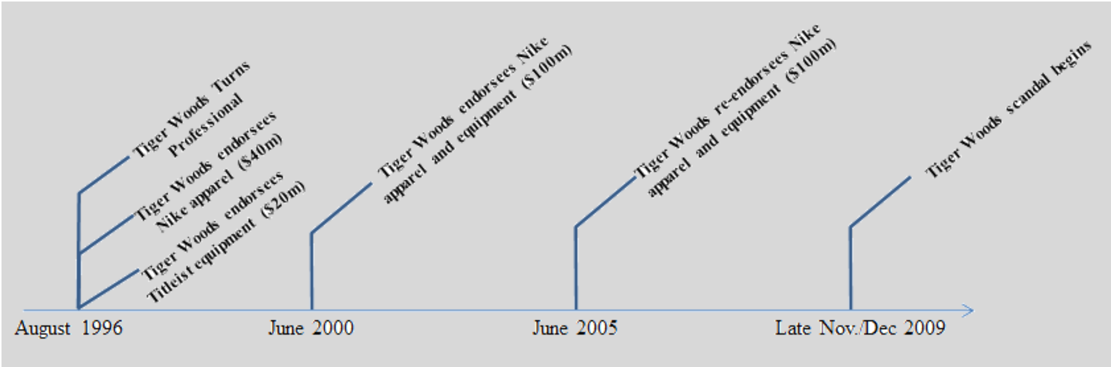

Figure 2.1: Tiger Woods Endorsement Time Line

Tiger Woods $200 million dollars ($181 million in 1997 dollars) to endorse its golf products. Figure 1 presents a time line of the above events.

2.2 Data and Descriptive Evidence

The data used in this study is aggregated monthly golf ball sales in the United States from February 1997 to April 2010. This data represents the total sales for the US for on course (green grass) and off course golf specialty stores. For on course shops, the sales represent a mix of public and private course golf shops. For off course, a mix of single owner and chains stores are represented. The figures are made up of over 550 on course shops and over 250 off course shops which are then extrapolated to an aggregate US level. There are a total of 669 unique products represented by a total of 26 different brands. Below are the summary statistics, plot of sales over time.

	On Course	**Off Course**	**Overall**
Average Price (per Dozen)	**$23.09** [$18.21,$26.37]	**$18.50** [$14.97,$22.33]	**$20.81** [$14.97,$26.37]
Units Sold (in Dozens)	**12,582** [4,415,25,441]	**12,573** [5,681,29,461]	**12,577** [4,415,29,461]
No. of Products Available	**61** [35,90]	**71** [41,102]	**66** [35,102]
No. of Brands Available	**13** [9,17]	**14** [10,17]	**14** [9,17]

Table 2.1: Summary Statistics for Each Market (Feb 1997 - April 2010)

Looking at the total sales of golf balls (unit in dozens) over time, it is apparent that the golf ball market exhibit seasonality and a time trend. Seasonality is expected as golf is a seasonal sport that takes place in warm climates. To take this into account, we include year month interaction indicator variables as well as manufacturer specific time trends in our estimation.

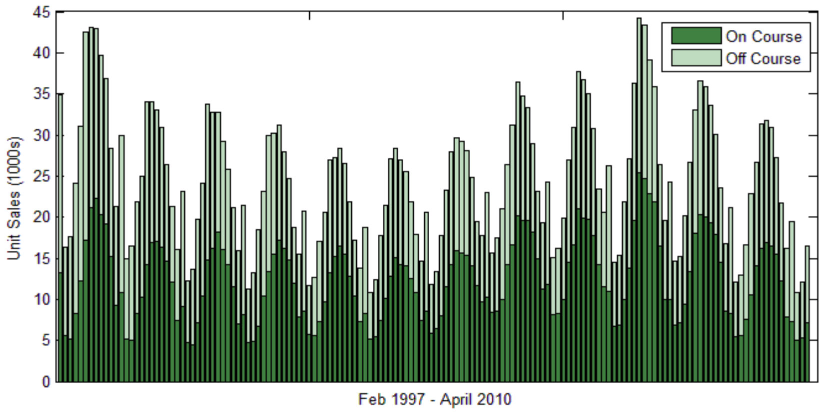

Figure 2.2: Total Golf Ball Sales (Dozens) for On and Off Course Shops

There are a large number of brands available in each month, ranging from 9 to 17. Likewise, the average number of products available in a given month is 66 with a minimum of 35 and a maximum of 102. It is also important to highlight the differences between the two respective retail channels, on and off course. First, there is a substantial difference between the mean price of a golf ball. This difference is a result of two important factors: a convenience premium and reduced competition given on course shops have less shelf space than do off course stores. This latter point being highlighted by the difference between the average number of products available in each channel, roughly 10 as shown on third row of Table 1.

Lastly, we present a cross sectional snapshot of market conditions for both the beginning and the end of the data period, April 2000 and April 2010 respectively for the off course retail channel. This will give the readers a quick synopsis of the changes in the golf ball market that we study. From the table below Titleist is "the number one ball in golf" followed by Top Flite, Pinnacle and Precept in 2000 and Callaway, Bridgestone and Nike in 2010. It is notable that Nike rose to become a major player by 2010 with the market share of 10%. We also present the Herfindahl–Hirschman Index (HHI) to determine the level of concentration/competition in the industry. The index corresponds to a relatively competitive industry which is corroborated by the four firm concentration ratio of 65.40 and 55.40 for 2000 and 2010 respectively.

2000				2010			
Brand	Share	Avg Price [Max Min]	#Products	Brand	Share	Avg Price [Max Min]	#Products
Titleist	23.51	$28.17 [$34.46 $22.32]	9	Titleist	23.08	$23.64 [$36.34 $15.34]	7
Top-Flite	22.74	$13.50 [$18.01 $10.23]	9	Callaway	11.75	$20.87 [$34.27 $8.37]	12
Pinnacle	11.63	$12.08 [$14.91 $9.75]	7	Bridgestone	10.57	$26.90 [$34.49 $17.67]	8
Precept	7.52	$22.82 [$31.44 $18.08]	9	Nike	10.00	$15.76 [$25.48 $8.60]	10
Wilson	7.52	$19.67[$26.94 $9.22]	11	Taylor Made	7.50	$21.32 [$36.29 $12.51]	6
Maxfli	6.23	$25.72 [$34.85 $14.28]	7	Top-Flite	7.14	$9.70 [$14.24 $6.20]	6
Strata	4.91	$24.79 [$25.64 $24.26]	3	Srixon	6.72	$21.02 [$32.35 $10.61]	7
Callaway	3.67	$39.68 [$40.30 $39.07]	2	Pinnacle	5.99	$9.60 [$12.22 $7.94]	6
Taylor Made	2.36	$31.36 [$33.97 $26.98]	3	Precept	5.79	$13.99 [$18.21 $8.02]	4
Spalding	2.35	$8.83[$26.98 $8.83]	1	Other	4.01	$8.61 [$8.61 $8.61]	1
Other	2.08	$13.24[$13.24 $13.24]	1	Wilson	3.00	$8.47 [$8.47 $8.47]	1
Dunlop	1.83	$11.59[$14.38 $10.04]	4	Noodle	2.26	$12.08 [$12.23 $11.93]	2
Nike	1.59	$26.48 [$36.39 $18.14]	4	Volvik	1.77	$15.79 [$15.79 $15.79]	1
Cobra	0.95	$21.22 [$22.85 $18.93]	4				
Srixon	0.51	$24.17 [$24.17 $24.17]	1			Note: Price is adjusted to 1997	
HHI	1417.03			1137.89			
Four Firm CR	65.40			55.40			

Table 2.2: Cross Sectional Market Conditions for April 2000 & April 2010 (Off Course)

It is also interesting to note that the total number of products available decreased, where in this particular market it goes from 75 products to 71. We also note that the average price dispersion has decreased, where for 2010 market it ranges from $8.47 to $26.90 whereas in 2000 it was $8.83 to $39.68. This brand level price trend however is not very informative as it is the average price for all "products" available, as indicated in the far right of the column.

To have a better idea of the price trend, we look at price in conjunction with time. Assessing intertemporal price variation is important because it allows us to glean into a consumer's decision process in this market. To be more precise, if we observe price drops over time, it is expected that some consumers may intertemporally substitute on the timing of their purchases. Below is a time series plot of the three major brands' prices. The plot is the average price of all products offered by a particular brand and the red vertical line represents when Tiger Woods' switch from Titleist (black) to Nike (blue). Note that the blue line does not start until 1999 as Nike Golf ball was not introduced until then. Similarly for Callaway (green) it was not introduced until early 2000. Looking at price, at least for Callaway, price looks to decrease over time, at least in the first 2 years. However, we note that this is due to the fact that Callaway entered the market with just two premium products (see table above) before releasing non premium products that drove down the average price. For Nike (blue), we find that there is an increase in price immediately after the switch by Tiger Woods before leveling off in the summer of 2002. Similar to Callaway, we observe a slight decrease initially in price because Nike also entered the market with premium products before releasing non premium products.

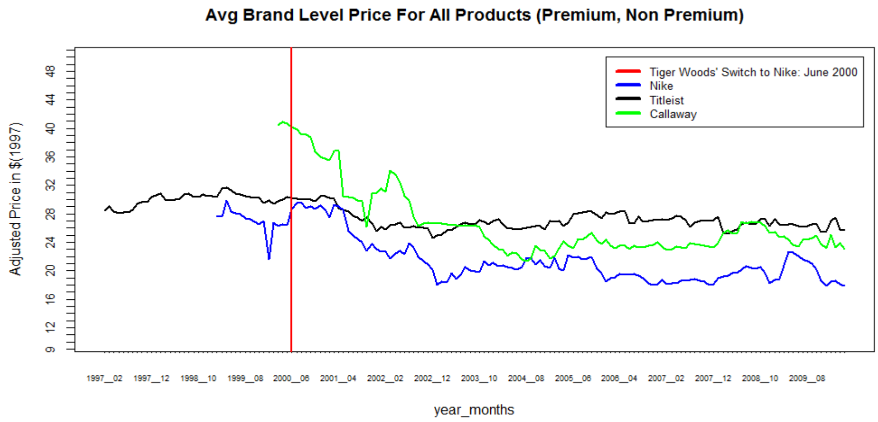

Figure 2.3: Plot of Brand Level Price Over Time

To empirically support the reasoning of our claim for why we see an initial decline in price for two brands (Nike, Callaway), we employ a subset of the data which consists of only "premium" products and plot the time series of average prices. As we can see below, the two brands' prices are now less drastic and more leveled. Furthermore, for Nike, even within the subset of the data, we again see a small increase in price after Tiger Woods' endorsement contract with Nike in June 2000. While we cannot attribute this to Tiger Woods, we will see in the counterfactual section that indeed the presence of his endorsement has an effect on a firm's pricing decision.

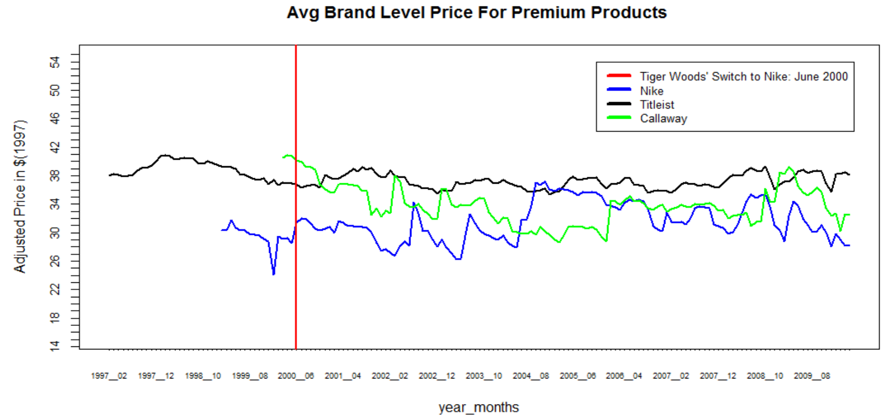

Figure 2.4: Plot of Brand Level Price Over Time for Premium Products

2.2.1 Nike Golf Ball Sales

In this section, we explore the data further by looking at the sales of Tiger Woods' endorsed brand Nike. Below we present the sales of Nike golf balls from its introduction in February 1999 until the end of our data period April 2010. The red vertical line represents June of 2000 when Tiger Woods made an official switch to the Nike golf ball. It is not difficult to see that even after taking into account the seasonality on sales over months, there appears to be a "jump" in sales for Nike Golf ball "post" Tiger Woods' switch.

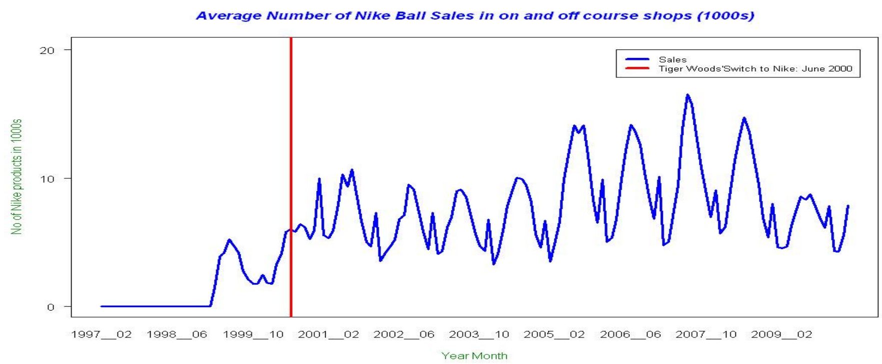

Figure 2.5: Total Sales of Nike Golf Balls (Dozens) Pre & Post Tiger Woods' Endorsement

Figure 5 zooms in on the date Tiger Woods switched endorsements by plotting market share of Nike Golf balls for the off course retail channel. Again the red solid vertical line represents the month in which Tiger Woods switched. To the left and right of this line are 18 months of market share pre and post his switch. This picture is quite clear in highlighting the discrete jump in market share for Nike in the month Tiger Woods switched as well as illustrate a significant growth in market share after he switched. Table 3 also presents similar results. It not only illustrates an increase in market share for Nike but also a substantial decline in share for Titleist.

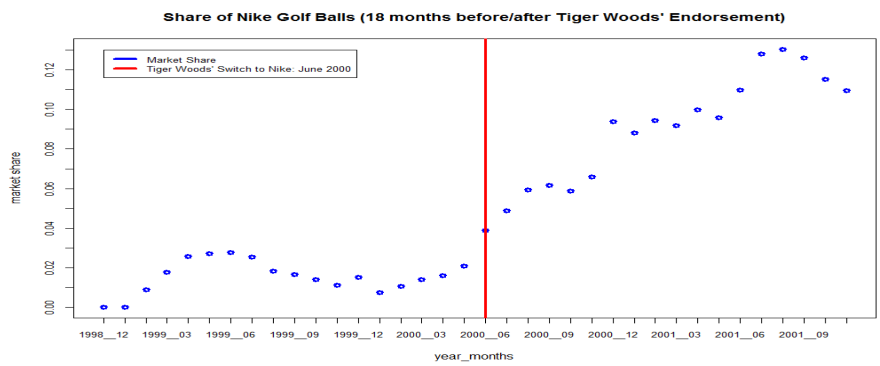

Figure 2.6: Share of Nike Golf Balls Pre and Post Tiger Woods Switch

	Before	After
Nike	1.5%	6.6%
Titleist	24.9%	21.8%

Table 2.3: Mean Market Share for Titleist and Nike 18 Months Pre and Post Tiger Woods Endorsement Switch (Off Course)

2.3 Reduced Form Analysis

We have shown through our raw data that Nike may have benefited from the signing of Tiger Woods to an endorsement contract in the form of increased sales and market share. These observations motivate a few important questions,

(1) Do endorsements increase sales?

(2) If so, how profitable are they?

Our strategy to identify the endorsement effect and to answer these questions is to use the exogenous variation in player ability, measured by a golfer's world ranking, and the variation in sales of the endorsed brand. With this, we employ reduced form analysis by running a regression to illustrate the potential causal effects of the exogenous ranking variable on sales. However, before we move to this analysis we first introduce some important variables which will be used in both our reduced form and structural models.

2.3.1 Celebrity Endorsement Effect

The impact of a celebrity endorsement can be decomposed into two distinct effects. Below we specifically discuss each. The first, a primary effect captures the quality of a player for the previous 104 weeks. The second effect or what we denote as a secondary or short term unplanned brand exposure effect is a result of an endorsing celebrity golfer winning a tournament in a given month. Specifically, in golf there are exposures that occur every week in golf tournaments from tournaments being broadcasted on television and we believe these brand level television exposures by golfers could be substantial and important in influencing the sales of golf balls each month. As we discuss below, we construct the unplanned brand exposure variable at the brand level based on the winners of the four monthly tournaments in each period t. The celebrity endoresement effect can therefore be written as a function of both the primary and secondary effects.

Primary Endorsement Effect

We capture the primary effect of celebrity endorsements on the sale of the endorsed brand by defining the (row) vector $\text{En}_{bt} = [E_{1bt}, E_{2bt}, E_{3bt}, ..., E_{Gbt}]$ for golfer g, brand b in market t where

$$E_{gbt} = \begin{cases} \left(\frac{1}{rank_{gt}}\right)^{\alpha} & \text{if} \quad D_{gbt} = 1 \\ 0 & \text{if} \quad D_{gbt} = 0 \end{cases} \tag{2.1}$$

Mainly, for each golfer g, given that the golfer endorses brand b, we define E_{gbt} as a function of the skill level at time t. D_{gbt} is the indicator variable which equals one if player g endorses brand b at time t. To take the quality into account, we use the inverse of the world ranking of the player g at time t as a proxy. Lastly, α measures the rate of decay of $\frac{1}{rank_{gt}}$. The ranking is determined accordingly:

"The World Ranking Points for each player are accumulated over a two year "rolling" period with the points awarded for each event maintained for a 13-week

period to place additional emphasis on recent performances – ranking points are then reduced in equal decrements for the remaining 91 weeks of the two year ranking period. Each player is then ranked according to his average points per tournament, which is determined by dividing his total number of points by the tournaments he has played over that two-year period. There is a minimum divisor of 40 tournaments over the two year ranking period and a maximum divisor of a player's last 56 events."[13][4] By taking into account the variability of skill level over time, we maintain that if there exist an endorsement effect, the effect will be larger when the player is of higher quality.

We include five golfers in our model; Tiger Woods, Phil Mickelson, Ernie Els, Vijay Singh and David Duval. We chose these five players because of the following reasons. All five players were ranked high in the world ranking for the majority of the time period between 1997 and 2010 with a clear record of these five players being under the endorsement contract with the respective company of the golf ball that they used.[5] Since our purpose is to study the impact of celebrity endorsements, we are interested in players who were top players on the PGA tour.[6] Perhaps one may think including just one celebrity would create an omitted variable bias problem. The rationale would be if another endorser also endorsed the same brand that Tiger Woods endorsed then not taking into account that endorser's effect would be problematic as the estimate will be biased upward. Our ranking data suggests that there is no strong correlation between endorsers who endorse the same brand and thus including only a subset of all golfers who endorse a brand is not problematic.

Secondary Endorsement Effect: Unplanned Brand Exposure from Celebrities Winning Tournaments

In order to create the secondary "unplanned" brand exposure variable we sum up the winning of golf tournaments by top golfers who endorse brand b in a given month. Therefore, our unplanned variable is at the brand level. This

[4]The Official World Golf Ranking is published every week, but given that we define our time in months, we use the end of the month's world ranking. http://www.officialworldgolfranking.com/home/default.sps

[5]An exception from these 5 players is David Duval, who ranked high from 1997 to 2003 before falling outside of the top 200 in rank. (He would come back in 2009 by being ranked in the top 200) We decided to include Duval in our estimation because not only do we know the date in which he switched from the Titleist product to the Nike product but during the time he was ranked high, he was considered as one of the the best golfer of all time.

[6]In fact, for players who were not consistently ranked high in their career, it was difficult to find out whether they had a formal endorsement contract with the golf ball that they used.

is “unplanned” exposure by top golfers because, in any given week (PGA golf tournaments occur once a week, four times a month), approximately 140~150 tour golfers participate in a tournament and anyone in the field has a chance to win. Therefore, from the brand’s point of view the exposure they may receive through the golfer using the firm’s product is “unplanned”. We agree that the probability of winning by the top players may be higher but it still holds true that from firm’s perspective, this exposure is random in a sense that it occurs with probability less than 1; mainly it is independent of the firm’s marketing strategy.

To briefly describe PGA tournaments, each tournament starts on Thursday of a given week with one round (18 holes) played each day for four days. In a four day competition, the person who scores the lowest accumulative strokes wins the tournament. Majority of the PGA tour tournaments are televised and usually the first two rounds are televised on a cable channel while the last two rounds are televised on regular network channel (NBC,ABC,CBS). In the last two rounds, the players that get the most coverage are those that are high up on the leader board. In all cases, as long as the player is on the top of the leader board in the final round, they will receive the most broadcast coverage, regardless of the world ranking of the player.[7] For viewers, it is not difficult to identify the product that golfers use as the camera angle allows the explicit view of the brands. For example, when a player is on the putting green, the camera would zoom into the golf ball capturing the roll of the ball to the hole from the view of the ground level.

We define the “unplanned” brand exposure variable as U_Ex$_{bt} = \sum_{g=1}^{P} EX_{gbt}$,

$$EX_{gbt} = \begin{cases} MWIN_{gt} + win_{gt} & \text{if} \quad D_{gbt} = 1 \\ 0 & \text{if} \quad D_{gbt} = 0 \end{cases} \tag{2.2}$$

Here, the win_{gt} is the indicator variable that is one if the player g at time t wins the tournament. Again, D_{gbt} is the indicator variable where it equals one if player g endorses brand b at time t. In the PGA Tour, there are 4 tournaments that are considered the “Major”. These include the Masters, US OPEN, British Open(The Open Championship) and the PGA Championship. These tournaments are usually widely publicized with typically larger audience and longer

[7]When Tiger Woods won the Masters tournament in April 2000, it was measured that he was on-screen for 32% of the broadcast time while the rest of the field was on for 36% of the time.[Grange]

TV coverage than regular tour tournaments. To take account for the extra exposure of these four major tournaments, we include the indicator variable $MWIN_{gt}$ where it equals one if the player who wins at t won one of the major tournaments. Therefore, we assign the major tournament to two while a regular tournament as one. We include three major golf ball manufacturers, Nike, Callaway and Titleist since at one point in their career, the top five players endorsed at least one of the three brands. For each firm, we match the historic PGA tour winner to the golf ball used from 1997 to 2010.[8]

One may argue that we can perhaps use a broader definition of the unplanned variable by taking into account all players who were in "contention" during the tournament coverage. While the top contenders during the week could have also received extra TV exposure, trying to take into account these players is difficult for the following reasons. First, determining the players who finished in top 5 from 1997 to 2010 is difficult because records of non winners are usually not readily available. Second, even if one obtains this information, we are hesitant on whether the top 5 players actually did receive the extra coverage that we know the winner received. This is because, it is not unusual to see players who end up in contention finish their final round of golf before the live coverage begins. Therefore, at best a highlight of their play are covered in the beginning of the coverage of the live broadcast. As the tee time for the final round of golf is determined by the reverse order of the accumulated rank of the first three days of tournament, where the leaders start last on Sunday afternoon, (time when the live coverage starts) we hesitate to make a broader definition of the unplanned variable as we are uncertain if the non winners received the exposure that we describe above.[9]

Below we tabulate the players that make up each brand's unplanned exposure variable.[10]

[8]While we made every effort to match the winners, in rare occasions we were not able to ascertain which ball the golfer would have used to win the tournament. This was especially the case for Titleist brand. In cases like this we left it as 0.

[9]Lastly, matching the player with the brand of product used is not always straightforward. Although we made every effort to determine this, there were instances even amongst the winners where determination of the brand of product used during tournament coverage was difficult. To this end, we limit ourselves to the winner of the golf tournament.

[10]Some players show up in multiple brands given that they switched their endorsed brand between 1997-2010. Also, we name only the top players for the Titleist brand given that there were significantly more players who won under Titleist brand than other brands on the PGA tour. This is expected since Titleist brand is the most widely used golf ball on the PGA tour. To name a few players we have included are winners like Ian Poulter, Hunter Mahan, Jason Bohn. For recent winners like these we used the PGA tour website with player profile that identifies whether Titleist golf ball was used.(http://www.pgatour.com/players/02/45/07/) For winners that

Nike	Titleist	Callaway
Tiger Woods	Tiger Woods	Phil Mickelson
David Duval	Phil Mickelson	Ernie Els
Stewart Cink	David Duval	
KJ Choi	Vijay Singh	
Trevor Immelman	Ernie Els	
Anthony Kim	Davis Love III	
Paul Casey	David Toms	
	Steve Stricker	
	Padraig Harington	
	...	

Table 2.4: PGA Winning as a Proxy for Advertisement Variable

We believe that unexpected brand exposure of golf ball products are highly unlikely to be correlated with the primary individual celebrity endorsement variable given exposure is also exogenous and is based upon who wins tournaments. However, erroring on the conservative side we include this variable as to control for the fact that perhaps player ranking and unplanned brand exposure are correlated. If we were to omit unplanned brand exposure the model error term would consequently be correlated with the endorsement variable and thus bias our estimate. Our inclusion of such term is motivated by a simple example. Suppose a brand b endorser increases his rankings over several months and does so by not winning. Also assume that during these months other players who have endorsement contracts with brand b and play brand b golf balls win several tournaments and generate unplanned exposure for brand b which lead to greater sales. Without accounting for the unplanned brand exposure variable the resulting primary endorsement effect would be over estimated as the two variables are positively correlated.

2.3.2 Planned Exposure: Advertisement Level Spending

We believe that traditional "planned" advertising exposure in major media outlets will vary over time and there is a possibility that this may influence our goal of consistently estimating the endorsement variables. This traditional "planned" method is where firms spend their marketing budget in different media outlets. For example, firms are likely to allocate different amount on TV, magazine, in-

trace back further, we made every effort to ascertain whether Titleist ball was used. For example, player like Brad Faxon, we were certain that he used Titleist golf ball to win tournaments.

ternet each month. While these budgets are usually determined months in advance, it is possible to have firms adjusting their marketing tactics as they see fit. If it is the case that these adjustments are present especially when an endorser's performance increases or a player wins a tournament, it is imperative that we capture the advertising effect to isolate out each celebrity endorsement effect on sales.

It is important to include in our specification the "planned" advertisement spending level by firms that use celebrity endorsements as a marketing strategy. This is because, one may argue that when the firm's endorser is ranked 1 then the firm is also likely to spend more on advertisements to highlight the fact that the product used by the world number one golfer is from that firm. Or, when a player wins a tournament and increases brand b's unplanned brand exposure the firm spends more on advertising to again highlight the players win.

We agree that advertisement level is an important component and if omitted it can potentially create omitted variable bias in our estimation. The concern is that if indeed firms are spending more when the endorser is performing better and if the advertisement level is omitted, then the error is now correlated with the endorsement variables. To control for the potential bias, we should include the advertisement level spending data that spans our data from 1997 to 2010. Unfortunately, given the long sales data of 13 years, we were unable to attain the advertisement level spending data for equal length. However, we were able to obtain a subset of the golf ball related advertisement level spending data that spans January 2003 to December 2009. Given this data limitation, we ran a pretest that allowed us to rule out with reasonable confidence the omitted variable issue.

To test our argument that "if the endorser is ranked 1 then the firm is also likely to spend more on advertisement" or "if unplanned brand exposure increases firms also increase advertisment," we run a regression that regresses the level of planned advertisement on the endorsement variables, 1/ranking and unplanned brand exposure variable, while controlling for seasonality. Our parameter of interest here are the endorsement variables as they would tell us if firms are indeed spending more on advertisement when the endorser is ranked higher in world ranking or a player wins a tournament. We find these varaiables to be not statistically significant as shown below. In fact, advertisement seems to be purely seasonal, occurring in the summer and spring months.

Parameters	Estimate	Std. Error
Brand Exposure	-44.99	91.85
1/Rank of Tiger Woods Nike	-736.19	653.14
1/Rank of David Duval Nike	919.38	11,823
1/Rank of Phil Mickelson Callaway	685.59	702.40
1/Rank of Ernie Els Callaway	-1,485.80	12824
1/Rank of Ernie Els Titleist	877.29	1,664.50
1/Rank of Phil MickelsonTitleist	-732.41	560.50
1/Rank of Vijay SinghTitleist	-1,281.10	1,120
Month2	605.71***	247.46
Month3	1707.10***	246.70
Month4	1410.90***	249.20
Month5	1205.40***	261.76
Month6	2094.40***	257.87
Month7	975.09***	260.76
Month8	644.79***	262.48
Month9	243.89	272.48
Month 10	-113.05	263.29
Month11	-159.74	258.73
Month12	-69.62	257.93

Note: Signif. codes: 0 < *** < 0.05< ** <0.1 Brand and Year FE not reported

Table 2.5: Regression of Planned Adv. on Truncated Data (2003-2010)

Having found that for 7 out of the total 13 years of duration there is no significant endorsement effect on "planned" exposure, we are reasonably confident that excluding the "planned" advertisement variable in our estimation on the full data set will not create an omitted variable bias problem.

Consequently, when we present the full structural model below we can either proceed and estimate a random coefficient model using the subset of the data where advertising data is available or we can take this test measure above to justify the reasonableness of omitting the "planned" advertisement level variable and estimate the model on the entire data set. We took the latter choice for three important reasons.

First, we believe that throwing away about half of the monthly data is certainly not desirable given the richness of month to month variation that this data presents us with. Second, it prevents us from identifying several celebrity endorsement variables we had originally included. Mainly, in a truncated data, we exclude two celebrities, Tiger Woods and David Duval both under Titleist golf brand. This is because both players endorsed the Titleist golf brand prior to 2003, our initial year of the truncated data. We want to point out that, it is imperative for us to keep the data prior to 2000 where we are able to estimate the endorsement effect of Tiger Woods on "Titleist" golf ball brand because this will allow us to run a more realistic counterfactual study to assess the economic value of celebrity endorsements. In other words, by separately identifying the endorsement of Tiger Woods in two brands under which he was in two independent multi-year contracts, we are able to run studies that ask interesting questions such as "What would have been Nike's profit if Tiger Woods stayed with the Titleist brand?" Lastly, the objective in this paper is to assess the economic value of celebrity endorsements, not measure the influence of advertisement on sales. To be more precise, our main concern for including advertisement in our specification is to control for the potential bias that can come from omission which we have shown above to likely not be the case.

2.3.3 Reduced Form Results

We now present reduced form work to motivate the use of 1/rank as our primary endorsement variable in our structural model below. These regressions illustrate that our primary endorsement variable is an appropriate measure to captures the impact of a celebrity on sales. We do so by regressing log of monthly sales (dozen of golf balls) on the main variable of interest, the exogenous endorsement variable ranking, while including controls for brand, year and month fixed effects. We transform the sales figure with natural logarithm as sales across brands are substantially different. For example while Titleist sold on average 577,000 dozen of golf balls per month from 1997-2010 and Nikesold on average of 117,000 dozen golf balls per month. Therefore, keeping the sales figure at levels, we would constrain the variables to grow by a fixed amount each month which in our case is inappropriate. By making this transformation, our estimates of the endorsement variable is interpreted as the proportional change in sales on a unit change of the regressor.

Before we present the results of our reduced form work we present a brief discussion regarding the identification of the primary celebrity endoresement effects. First, what enables us to determine a celebrity's effect is the presence of endorser quality data and the fact that it exogenously varies over time. Specifically, to identify such an effect we make the assumption that as a celebrity's quality level decreases the endorsement effect he possesses decreases. Thus, the co-movement in a player's random peformance over time and brand sales allows us to identify a celebrity's causal effect on sales after controlling for any correlation between brand exposure and player quality. Again, what enables us to determine such an effect is the presence of exogenous endorser quality data and the fact that brands do not increase planned advertising as celebrity quality increases or celebrities win tournaments.

Our first regression consists of aggregating sales up to the brand level and restricting the data to only include Nike and Titielist since these are the two brands Tiger Woods has endorsed over his career. We also omit a portion of sales data when Tiger Woods was not a part of an endorsement deal with either brand. We report our results in Table 6; we excluded the month and year fixed effects to preserve space.

Regression of Log(Sales) on Parametric Endorsement Variable $\left(\frac{1}{rank}\right)^{\alpha}$						
	$\alpha = 1$	$\alpha = 0.5$	$\alpha = 0.4$	$\alpha = 0.3$	$\alpha = 0.2$	$\alpha = 0.1$
Unplanned Exposure	0.022 (0.014)	0.022 (0.014)	0.021 (0.014)	0.021 (0.014)	0.021 (0.014)	0.021 (0.014)
1/rank of Tiger Woods	0.127 (0.057)**	0.181 (0.087)**	0.205 (0.101)**	0.245 (0.124)**	0.3257 (0.210)	0.566 (0.310)
Brand Fixed-Nike	4.059 (0.084)**	4.000 (0.107)**	3.979 (0.120)**	3.939 (0.140)**	3.858 (0.184)**	3.616 (0.318)**
Brand Fixed-Titleist	6.383 (0.107)**	6.328 (0.127)**	6.303 (0.137)**	6.262 (0.156)**	6.182 (0.196)**	5.941 (0.3271)**
Adjusted R^2	0.9796	0.9794	0.9793	0.9793	0.9793	0.9792

Note: Estimate (standard error) significance Sales is in 1000's of dozen Balls

Signif. codes: 0 < ** < 0.05

Table 2.6: Regression of Log(Sales) on Parametric Endorsement Variable

As shown above from the R^2 statistics, the model with $\alpha = 1$ generates the largest adjusted R^2 with 98% of the variance being explained by the regressors. For the variable of our interest, we see that the exogenous world ranking variable of Tiger Woods is statistically significant. This estimate suggests that in the presence of Tiger Woods endorsing a golf ball brand and moving from rank two to number one in the world, the model predicts that the proportional change in sales is 6.5% (0.127/2). Also notice the unplanned brand exposure variable is insignificant. The model is consequently attributing all the impact of the endorser to the primary endorsement effect (the rank variable) and not to the secondary effect associated with a spike in unplanned brand exposure from a celebrity winning. A similar result is found below were we specifically look at the impact endoresements have on levels of Nike golf ball sales.

We complete our reduced form analysis by looking exclusively at Tiger Woods' effect on Nike golf ball by regressing Nike sales during the time period in which Tiger Woods was an endorser on the golfer's ranking. While one can get a sense of the proportional change in Nike golf ball sales from the above analysis, we run a separate regression on level sales to estimate the additional quantity of dozen golf balls sold through Tiger Woods' endorsement effect again month and year fixed effects are not reported.

Regression of Sales on Parametric Endorsement Variable $\left(\frac{1}{rank}\right)^{\alpha}$						
	$\alpha = 1$	$\alpha = 0.5$	$\alpha = 0.4$	$\alpha = 0.3$	$\alpha = 0.2$	$\alpha = 0.1$
(Intercept)	23.406 (21.317)	-3.550 (31.895)	-17.209 (37.558)	-40.059 (47.233)	-85.887 (67.004)	-223.627 (127.294)
1/rank of Tiger Woods	41.033 (17.682)**	67.997 (29.590)**	81.659 (35.622)**	104.511 (45.710)**	150.340 (65.941)**	288.083 (126.740)**
Unplanned Exposure	0.893 (3.642)	.8270 (3.644)	0.831 (3.644)	0.835 (3.645)	0.839 (3.645)	0.843 (3.646)
Adjusted R^2	0.9030	0.9029	0.9028	0.9028	0.9028	0.9028

Note: Signif. codes: 0 < ** < 0.05

Table 2.7: Regression of Nike Golf Ball Sales (1000's of dozen Balls)

We find that the exogenous ranking variable (1/rank) has a significant effect on sales of Nike golf balls. And again, the model with $\alpha = 1$ provides the best fit to the data. Given that the sales are in 1000s of dozen balls and each observation corresponds to a month, the regression output above suggests Tiger Woods' effect on Nike sales is is 20,517 additional dozen of golf balls sold when he goes from number 2 in the world to 1. In the online appendix we also include additional results which assume a non parametric form for the exogenous ranking variable that estimates the effect of each rank while preserving the rank order model to further highlight and support the role celebrity quality has on brand sales. From all of these results we determine the parametric model with a decay rate equal to one is the best fitting and most appropriate model.

In this section we provide a preliminary analysis of the impact celebrity endoresements have on sales of golf balls. We were able to estimate and show the endorsing golfer's ranking variable is the primary endorsement effect and is an appropriate measure for capturing such an effect.

2.4 The Structural Model

We now introduce our main model. The main advantage of the structural model is that it allows us to run policy scenarios where we are able to subtract the additive separable endorsement effect in the consumer's utility function and add it to a different firm that may have otherwise signed an endorsement contract with the golfer. This allows us to test how the market would have reacted if one endorser had endorsed a different brand. Additionally, by modeling consumer demand in a structural framework, we will be able to assess not only the magnitude of the benefit of celebrity endorsement in dollars amount but also the source of this benefit (primary demand and business stealing effect) taking into account the competitors reaction to celebrity endorsements (pricing decision). This is important as it can answer the two questions posed above in a more realistic fashion while allowing us to have a better understanding of the mechanism by which celebrity endorsements affect the market. In our context, we can study the scenario where Tiger Woods would have stayed with his first endorsed firm Titleist where the endorsement effect would have stayed with Titleist products rather than shift to Nike. By performing this exercise, it allows us to assess whether it was a profitable strategy for Nike to invest $200 million ($181 million inflation adjusted) for 10 years.

We posit that endorsements play a direct role in a consumer's utility function when consuming the endorsed brand. We borrow from Bagwell and assume celebrity endorsements take a complementary view where a consumer's consumption process can either be enhanced or worsened through additional or negative utility attached on the endorsed brand. The complementary view is different from the persuasive and informative views. The complementary view does not make a distinction between the endorsement containing any information or influence of consumer behavior. Moreover, the complementary view allows for alternative explanations such as consumers may value social prestige associated with the consumption of a brand a celebrity endorses.[14]. Newman, Diesendruck and Bloom (2011)[15] show consumers value celebrity products through contagion. With this view, we predict that endorsements in and of itself can alter demand and increase or decrease, due to a celebrity scandal, a firm's market share.

The underlying theory behind our model construct originate from Stigler and Becker (1977)[16] and Becker and Murphy (1993)[17] in which they analyze models that incorporate a brand's advertising level into a consumer's utility function. When such an interaction is positive they find that the likelihood of consumption increases. Moreover, *"advertising can in itself create prestige, differentiation, or association that may change the utility a consumer obtains from consuming a product".[18]* This line of literature is closely related to our study in that one may think of the quality of a celebrity endorser as the analog to their advertising levels. It must be noted, however, that we make a clear distinction between endorsement and advertisement. We define the endorsement effect as the overall effect the endorser has on the company during the time period in which he is under contract. For an advertisement effect, we define it as the overall brand (planned and unplanned) exposure effect in the media at a given time.

Given the aggregated nature of the data structure, our approach is to jointly estimate the demand and supply by following the methodology of Berry, Levinsohn and Pakes (1995)[19] but with implementation of Skrainka and Judd's (2011)[20] quadrature approach to more efficiently and quickly calculate market shares.

We include the supply equation in the estimation because we want to recover the marginal cost as it will be necessary later in the counterfactual section when we calculate profit. Furthermore, having the supply side will allow us to study the pricing decision of firms in the presence and the absence of celebrity endorsements. We are cognizant of the advantage and the disadvantage of including the supply side. From the estimation point of view, the supply side gives us additional moment conditions that allow us to recover the marginal cost. On the other hand, this additional assumption can lead to demand estimation that is misleading. This often leads the researchers to assume a marginal cost rather than estimating it.

We show that including the supply side does not significantly affect our estimates by estimating both a demand only model as well as a demand and supply model.

2.4.1 The Demand Side

We define a market as the national golf market for each month from February 1997 to April 2010 for both on and off course golf shops. We assume that the market size for the golf ball market is 40 million per year.[11] The indirect

[11] We make this assumption based both on the size of the population of golfers and the quantity of products sold in each market while maintaining a large enough market to allow for a non zero

utility of consumer i from consuming a dozen of j golf balls from brand b in market t is characterized by K different golf ball characteristics in matrix X, price $p_{j_b t}$, endorsement brand vector En_{bt} and "unplanned" brand exposure variable U_Ex_{bt-1}. We are also interested in studying the effect of Tiger Woods' scandal and we are able to do so by including the vector Nike x Sc_t where Nike is an indicator variable for all Nike products and $\text{Sc}_t = [S_{first\,2}, S_{last\,3}]$ where $S_{first\,2}$ is an indicator variable for the first two month post the scandal. (December 2009, January 2010). Similarly, $S_{last\,3}$ are the following three months, February to April of 2010, the end of our data point. By defining the scandal variable of Nike products in two time periods, we are able to separately identify the scandal effect on Nike golf ball sales immediately after the scandal as well as during the last three months of our data periods. Furthermore, we include year month fixed effect variable TD (dummy of year month interaction) and firm specific time trend matrix **F_Tr**. Our inclusion of the TD variable is to control for any time specific demand shock that comes from seasonal nature of the sport of golf. We include firm specific time trend to capture any trend on firm value/performance that may increase or decrease over time. By including these two variables, the scandal variable Sc_t captures the impact of sales during the scandal period above and beyond the general time specific shock from seasonality as well as general firm specific trend that may be present during those months. Lastly, the utility is characterized by the unobservable (to the econometrician) product and time specific characteristics $\Delta\xi_{j_b t}$ and individual taste parameter $\varepsilon_{ij_b t}$, distributed i.i.d. type 1 extreme value across i, j and t. Note in estimation we include product specific fixed effects rather than product characteristics such as number of layers a ball has or how many dimples it has since these characteristics are time invariant. For example, Titleist's Pro V1 characteristics of 392 dimples and 3 layers construction have been invariant since its introduction in late 2000 to April 2010, the end of our data period.[12] It is usually

outside share. In the appendix we include a detailed discussion regarding how we determine the potential market size to be 40 million people and also provide sensitivity analysis around this measure.

[12]Pro V1 has produced "newer" version of the golf ball approximately every 2 years since its introduction. While the main characteristics have remained constant over the years, the packaging has slightly changed (color and graphics) while each golf ball has a unique side stamp that designates the time in which the golf ball was produced. For example, Pro V1's very first production had a side stamp of "Pro V1 392" from 2000-2001 followed by "<Pro V1 . 392>" between February 2001 to January 2003. The latest Pro V1 has a side stamp of "<.—Pro V1—.>" designating the introduction in February 2009. For more information,
http://www.titleist.com/teamtitleist/team-titleist/f/5/p/4578/18058.aspx#18058

the case that in the golf ball market, when the essential product characteristics change, the product name also changes.

Consumer i's indirect utility for golf ball j in market t is,

$$u_{ij_bt} = X_{j_bt}\beta_i + \alpha_i p_{j_bt} + \mathbf{En}_{bt}\Gamma + \mathbf{U\_Ex}_{bt-1}\lambda + (\mathbf{Nike\ xSc}_t)\Upsilon + \kappa TD + \mathbf{F\_Tr}\Xi + \Delta\xi_{j_bt} + \varepsilon_{ij_bt} \tag{2.3}$$

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix} + v_i\Sigma \qquad v_i \sim N(0, I_{K+1}) \tag{2.4}$$

For golf ball price p_{j_bt}, we adjust the price to 1997 dollars. Here $\bar{\alpha}, \bar{\beta}$ are mean marginal utilities toward price and product characteristics while Σ is the estimate of the standard deviation of our random coefficients. The model parameters of interest consists of both linear and nonlinear parameters. The model parameters are $\theta = (\theta_1, \theta_2)$ where the vector $\theta_1 = (\overline{\alpha}, \Gamma, \lambda, \Upsilon, \kappa, \Xi)$ contains the linear parameters while $\theta_2 = \Sigma$ is the nonlinear parameter. Consumers are assumed to purchase one unit of goods in each period that gives the highest utility, including the outside option which is normalized to zero.

We now elaborate on the unobservable product and time specific characteristics $\Delta\xi_{j_bt}$. In absence of product and year month fixed effect, we have ξ_{j_bt} rather than $\Delta\xi_{j_bt}$ which its interpretation is a standard unobserved product characteristics. By including the product and year month fixed effect we have essentially decomposed the unobserved component in the following way,

$$\xi_{j_bt} = \underbrace{\xi_{j_b}}_{Product\ Fixed} + \underbrace{\xi_t}_{Time\ Fixed} + \Delta\xi_{j_bt}.$$

2.4.2 The Supply Side

The market we study is an oligopoly with multi-product firms. Assuming that the observed prices are the result of an interior, pure strategy Bertrand-Nash equilibrium, we can make use of the information from the first order conditions of profit maximization. Mainly, given the profit function for firm F,

$$\pi_{Ft} = \sum_{j \in F} M \cdot s_{jt}(p_{jt} - mc_{jt})$$

where M is the market size, s_j product j market share which is produced by firm F, mc_j is the marginal costs for firm $F's$ product j we write the first order condition of the above profit function with respect to product j price as:

$$M\{\sum_{r \in F}[p_j - mc_j][\frac{\partial s_{rt}(\mathbf{x}, \xi, \mathbf{p}, \theta_d)}{\partial p_{jt}}] + s_{jt}(\mathbf{x}, \xi, \mathbf{p}, \theta_d)\} = 0$$

Since we observe p_j and θ_d is the parameter from the demand side which we estimate we are able to compute the marginal cost mc_j. We assume that the marginal cost decomposes into an observable w_{jt} and unobservable component ω_{jt} (to the econometrician), $mc_{jt} = w_{jt}\gamma + \omega_{jt}$ with γ being the vector of parameters to be estimated. In our case, we define w_{jt} as a matrix consisting of vectors of golf ball characteristics (material cover, layers, dimples), firm indicator, channel indicator, a firm specific time trend and time dummy variables. We assume that the observed component w_{jt} is uncorrelated with ω_{jt}. However, for the markup which is a function of market share, we use the predicted markup and the predicted market share from the demand side as instruments. As the predicted markup from the demand side is a function of exogenous variable and the instruments for price, we are effectively instrumenting for the markup with demand shifters.)[21]

2.4.3 Identification

Identification of the Endorsement Parameters

Our identification of the endorsement parameters orginiates from the exogenous variation of a celebrity's quality (a player's monthly rank in the world golf ranking system). What identifies the causal effect of the endorsement is the connection between product sales and a player's random performance over time. By defining golfer g's primary endorsement variable as an inverse of the world ranking of that golfer at time t we are assuming that the primary endorsement effect would approach zero as ranking goes to infinity. Also note that we allow this primary endorsement effect to vary by player and sponsor. For instance, we allow Tiger Woods' impact to differ for Nike and Titleist.

We argue that we do not suffer from the endogeneity bias that arise from the primary endorsement variable being correlated with $\Delta\xi_{j_b t}$, given $\Delta\xi_{j_b t}$ are likely random demand shocks. However, if we more narrowly interpret $\Delta\xi_{j_b t}$ to be the product specific time varying promotion or marketing campaign then it is possible that our primary endorsement variables are correlated with the error term. An example of a manufacturer promotion would include "mail in rebate", "buy a dozen of golf ball get a free fleece jacket" type of promotion that occurs at a product level. Under this narrow interpretation firms might well possibly be managing these promotions so that they time them with celebrity movement in their performance. We believe this to be quite unlikely. Our reasoning is based on the analysis we ran above regarding the firms dynamically adjusting advertising. Table 5 again presents results from a regression of advertising levels on celebrity endorsement variables and month fixed effects. We see from these results that firms do not adjust advertising spending with movement in player performance. Advertising appears to be only a function of the month of year. With such evidence for advertising not being correlated with player performance over time it is unlikely that firms would be adjusting promotional or other marketing campaign tatics with player performance. The concern regarding endogenity bias of our primary endorsement effects is therefore mitigated with either interpretation a reader makes with regard to $\Delta\xi_{j_b t}$. Also note the indentical argument can be made to identify the secondary endorsement effect or unplanned brand exposure from celebrities winning. Again, our concern is that firms adjust advertising or promotions to coincide with a player winning a tournament creating correlation between the secondary endorsement effect and the model error term. Table 5 presents results that eliminate such a concern by presenting an insignificant parameter estimate for brand exposure.

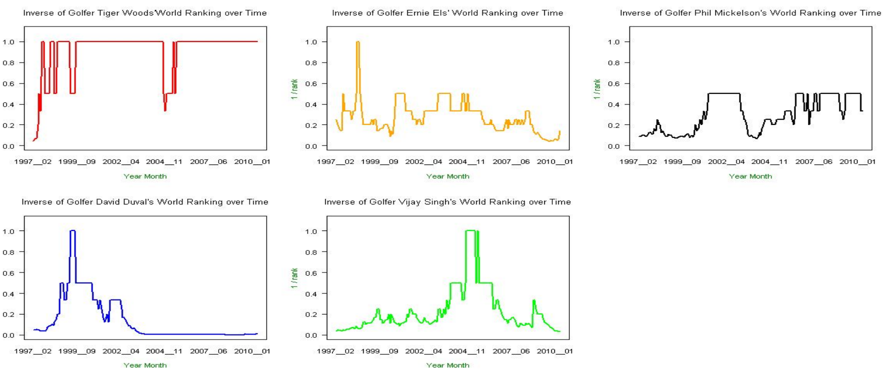

Figure 2.7: Inverse of World Ranking of Celebrity Endorsers

Instrumental Variables for Price Endogeneity

We assume that the explanatory variables less the price variable p are uncorrelated with the error term $\Delta\xi_{j_b t}$. Therefore, we allow these variables to instrument for themselves. For p however, we look for variables that shift cost or margins that are not correlated with the demand shock $\Delta\xi_{j_b t}$. We have five instruments following closely the type of instruments used in the original Berry, Levinsohn and Pakes (1995)[19] which captures how competitive the market is in product space. For instance, greater number of products which share the same number of layers of balls face greater price competition. Our instruments are: total number of competitiors' products in period t, total number of firm f's products, off course shop indicator, sum of competitors' layer characteristic and the sum of own firm's layer characteristic.[13] Now although these instruments are standard in the empirical IO literature it is important to understand that it is plausible that unobservables are driving firm selection of product characteristics. However, it is typically recognized that changes in product characteristics are difficult and time consuming to implement. Thus, the use of these intruments are only valid if we assume firms cannot adjust product characteristics in each period. Lastly, since we have two separate markets with an observed price premium for on course shops, we include the Off Course Shop indicator variable as an instrument for price. This variable captures the mean relative difference in marginal cost across channels for all products. The first stage of the 2SLS is included below, reporting just the estimate of the excluded instruments for price to preserve space.

[13] We also run a model with the lag measure of the total number of a firm's products and find the results do not differ.

First Stage Regression (Price~IV+X)	
	Estimate
Number of competing products	7.618 (0.661)**
Number of own products	7.379 (0.661)**
Off Course Shop	-4.219 (0.041)**
Sum of Competitor's layer	-0.052 (0.004)**
Sum of own firm's layer	-0.044 (0.007)**
F-stat=5805.75	

Note: Signif. codes: 0 < ** < 0.05

Table 2.8: First Stage of 2SLS

We show that all of the instruments are statistically significant while 95% of the price variation is explained by the regressors. Additionally, we test for the strength of the instruments by running an F-test. From this test we conclude are instruments are strong. To satisfy the exclusion restriction, these variables must first not enter the demand equation and second be uncorrelated with the unobservable product characteristics $\Delta\xi_{j_bt}$. We argue that these variables do not belong in the demand equation because consumer i's utility is not dictated by the state of "competition" for product j in market t. In fact, while our institutional knowledge tells us that consumer $i's$ utility from product j is a function of the type of material, layers, and even brand loyalty on product j, which we capture through product specific fixed effect variable PD, the relative competition of a particular product's layer as well as the level of product diversification of a particular manufacturer is not part of their decision process. For Off Course shop indicator variable, as mentioned in the data section, it is clear that there are mark-ups on golf balls sold in on-course pro shops. In fact, the same product offered in off course shops command price premium in on course shops. For this reason, the Off Course Shop variable is a good instrument since it is correlated with price yet not with the demand shock.

2.4.4 The Moment Conditions

We have two sets of moment condition coming from the demand and the supply side equation. The demand side moments are, $E[\Delta\xi' Z^d] = 0$ where $\Delta\xi = [\Delta\xi_1, ...\Delta\xi_T]'$ where $\Delta\xi_t$ is a J dimensional vector of $\Delta\xi_{j_bt}$ where j is the product (j=1..J) in market t (t=1,..T), $\Delta\xi_{j_bt} = \delta_{jt} - (\alpha p_{jt} + \text{En}_{jt}\Gamma + \text{U\_Ex}_{t-1}\lambda + (\text{Nike xSc}_t)\Upsilon +$

$\phi PD + \kappa TD + \text{F\_Tr}\Xi)$. δ_{jt} is recovered by equating the predicted and the observed market shares for product j in market t through the contraction mapping. $Z^d = [z_p^d, Rd]'$ where $Rd = [\text{En}, \text{U\_Ex}, \text{Nike x Sc}, PD, TD, \text{F\_Tr}]$ and z_p^d is the demand side instruments.

The supply side moment are, $E[\omega' Z^s] = 0$ where ω is a vector of marginal cost error terms and $Z^s = [\widehat{\text{markup}}^d, w]'$. More specifically, $\widehat{\text{markup}}^d$ is the estimated markup while w is the regressor for the supply equation. With the addition of the supply side, we form additional moment conditions and jointly estimate the parameters of the demand and the supply side equation. Because the marginal cost is a function of markup which in turn is a function of the price sensitivity parameter α, by forming the supply side moment condition and estimating the parameters jointly, it allows the estimation to take into account the cross-equation restrictions on the parameter of interest.

2.5 Estimation Results

We estimate the model using generalized method of moments (GMM) as part of a nested fixed-point algorithm matching the simulated market share to the observed market share and forming moment conditions. As a benchmark, we first estimate the logit model with and without the instrumental variables. The estimation procedure and result are in the appendix. For the proposed random coefficient model, to save space, we do not report the estimated values PD, TD and F_Tr. However, they were statistically significant.

Random Coefficient Model				
	(Supply and Demand)		(Demand)	
Linear Parameters	**Estimate**	**SE**	**Estimate**	**SE**
Winning of Tournaments (unplanned exposure)	0.023	0.015	0.021	0.014
Woods Scandal on Nike products (12.2009-01.2010)	-0.037	0.090	-0.044	0.089
Woods Scandal on Nike products (02.2010-04.2010)	-0.169	0.094	-0.180	0.093
Woods Nike Endorsement	0.301 **	0.079	0.302 **	0.079
Duval Nike Endorsement	-0.364	0.247	-0.387	0.244
Mickelson Callaway Endorsement	1.284 **	0.207	1.299 **	0.206
Els Callaway Endorsement	1.289 **	0.311	1.357 **	0.311
Woods Titleist Endorsement	0.271 **	0.076	0.291 **	0.074
Mickelson Titleist Endorsement	-0.329	0.194	-0.340	0.192
Duval Titleist Endorsement	0.484 **	0.108	0.488 **	0.106
Singh Titleist Endorsement	-0.117	0.094	-0.121	0.093
Els Titleist Endorsement	0.664 **	0.138	0.668 **	0.136
Non Linear Parameters	**Estimate**	**SD**	**Estimate**	**SD**
Price	-0.088 **	0.021 **	-0.089 **	1.71E-08
	(0.003)	(0.008)	(0.008)	(9.984)
Layers		-4.362e-08		-2.17E-07
		(547.839)		(1438.543)

Note: Signif. codes: 0 < ** < 0.05; Supply side estimates available upon request

Table 2.9: Estimate of the Random Coefficient Model

As shown in Table 9, Tiger Woods' endorsement effect on both Nike and Titleist products are statistically significant with the estimated coefficients of 0.301 and 0.271 respectively. This suggests that Tiger Woods had the endorsement effect on all Titleist products between 1997 to 2000 and all Nike products during the endorsement period 2000-2010 by contributing to additional utility attached to the respective brand products. Amongst other golfers, it is interesting to note that Ernie Els and David Duval had a larger marginal impact for Titleist brand at 0.664 and 0.484 respectively than Tiger Woods' 0.271. We point out that this is a marginal effect, and since the endorsement effect is a function of the inverse of the world ranking, Tiger Woods' effect is larger in majority of the time in our data period. We point out that the endorsement effect disappears when David Duval endorses Nike. If one is familiar with the context of David Duval as a player it is not difficult to understand this phenomenon. David Duval's dramatic decline in performance as a golfer is a well known story in the golf community. In fact, it was around the time when David Duval switched to Nike in the 2001-2002 season did his skill level drop significantly. This result exemplifies our source of identification where the endorsement variable approaches

0 as the ranking of the player approaches infinity. Since we explicitly take into account the variability of skill level for each players through the world ranking, this result confirms our belief that David Duval's fall as a top athlete should have caused the drastic change in the impact he had on the new endorsed product Nike. We also find statistically significant results for another golfer Ernie Els. For Ernie Els, who switched to Callaway in 2007, he was an effective endorser under Titleist at 0.664, and this marginal effect became greater when he endorsed Callaway products.

A random coefficient was set on price and the golf ball characteristic layers. As expected, we find customer heterogeneity in price sensitivity but none in regard to layers. With the average price sensitivity of -0.088 per dollar, 95% of the consumers are estimated to have marginal price sensitivities between -0.130 and -0.046. In the below table we present elasticities for a subset of golf balls sold via on course golf shops in June 2007. We use this table as a sanity check to determine first whether our result are reasonable and two that the model we impose is consistent with a profit maximizing firm that sets price on the elastic portion of the demand curve. From this table we see that all cross price elasticities are positive while own-price elasticities are less than negative one indicating the results are reasonable and consistent with a profit maximizing firm.

Lastly, for the supply side we estimate the parameters of marginal cost. We find that our regressors are all significant with sign and magnitude that correspond with our prior knowledge of the production process being affected by firm and ball characteristics. For example, we find that Layer estimate is positive and significant which is in line with our knowledge that the cost to produce multi-layer balls are more expensive than two layer balls. In fact, while institutional knowledge estimates marginal cost of a dozen of golf ball as $4-$8, our model estimates show that the average marginal cost for a dozen of golf ball is $7.34, an indication of good model fit. We include the estimate in the appendix since they provide little pertinent information outside aggregate marginal cost which we use in the counterfactuals.

Price Elasticity On Course Shop 2007.06																		
TITLEIST PRO V1	-2.672	0.383	0.366	0.365	0.361	0.379	0.379	0.382	0.364	0.380	0.362	0.373	0.374	0.360	0.377	0.375	0.354	0.354
TITLEIST PRO V1x	0.247	-2.824	0.236	0.235	0.233	0.245	0.244	0.246	0.235	0.246	0.234	0.241	0.241	0.232	0.243	0.242	0.228	0.228
TITLEIST NXT TOUR	0.129	0.129	-1.914	0.134	0.134	0.130	0.130	0.129	0.134	0.129	0.134	0.131	0.131	0.135	0.130	0.131	0.136	0.136
TITLEIST NXT	0.114	0.114	0.119	-1.861	0.120	0.115	0.115	0.114	0.119	0.115	0.120	0.117	0.117	0.120	0.116	0.116	0.122	0.122
TITLEIST DT SOLO	0.088	0.088	0.093	0.093	-1.667	0.089	0.089	0.088	0.093	0.088	0.094	0.091	0.091	0.095	0.090	0.090	0.096	0.096
BRIDGESTONE TOUR B330	0.012	0.012	0.011	0.011	0.011	-2.819	0.012	0.012	0.011	0.012	0.011	0.012	0.012	0.011	0.012	0.012	0.011	0.011
BRIDGESTONE TOUR B330-S	0.003	0.003	0.003	0.003	0.003	0.003	-2.806	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
CALLAWAY HX TOUR	0.016	0.016	0.015	0.015	0.015	0.016	0.016	-2.967	0.015	0.016	0.015	0.015	0.015	0.015	0.016	0.016	0.015	0.015
CALLAWAY HX TOUR 56	0.024	0.024	0.025	0.025	0.025	0.024	0.024	0.024	-1.944	0.024	0.025	0.025	0.025	0.026	0.025	0.025	0.026	0.026
NIKE ONE PLATINUM	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	-2.896	0.015	0.015	0.015	0.015	0.015	0.015	0.014	0.014
NIKE ONE BLACK	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.004	0.003	-1.841	0.004	0.004	0.004	0.003	0.004	0.004	0.004
NIKE OTHER	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	-2.488	0.002	0.002	0.002	0.002	0.002	0.002
SRIXON Z-UR	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	-2.514	0.003	0.003	0.003	0.003	0.003
SRIXON Z-URS	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	-1.689	0.002	0.002	0.002	0.002
TAYLORMADE TP BLACK	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	-2.702	0.008	0.008	0.008
TAYLORMADE TP RED	0.011	0.011	0.010	0.010	0.010	0.011	0.011	0.011	0.010	0.011	0.010	0.010	0.010	0.010	0.011	-2.586	0.010	0.010
TOP FLITE D2 DISTANCE	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.004	0.003	0.004	0.004	0.004	0.004	0.003	0.004	-1.281	0.004
TOP FLITE D2 FEEL	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.003	0.004	0.003	0.004	0.004	0.004	0.004	0.003	0.004	0.004	-1.283

Table 2.10: Price Elasticities of Top Brands

Note: Change in Market share for product i with 1% change in price of product j where i=row, j=column.

2.6 Counterfactuals

By incorporating the endorsement and unplanned exposure levels into the consumer's utility function, we found that consumers attach additional utility to celebrity endorsed brands. In this section we first look at the overall effect of celebrity endorsements in the golf industry. Mainly, we want to assess whether or not endorsements can also *"create prestige, differentiation, or association that may change the utility a consumer obtains from consuming a product."[18]*(Ackerberg 2001) Once we show that celebrity endorsements generate shifts in market share, we assess the economic value of celebrity endorsements by looking specifically at Tiger Woods.

2.6.1 Product Differentiation Through Celebrity Endorsements

Our demand estimate suggests that there are statistically significant celebrity endorsement effects attached on endorsed brands. Given this finding, we assess whether the extra utility attached to the endorsed brands are large enough to generate shifts in market share. We first want to assess the overall endorsement effect in the golf market. To do so, we run the counterfactual by assuming that no celebrity endorsements exist in the golf industry and compare it with a regime where celebrity endorsements exist in the industry.

	Change in Share
Nike	0.013
Titleist	0.031
Callaway	0.015
Others	-0.025
Outside Option	-0.034

Table 2.11: Change in Share with the Presence of Endorsement

As shown, we see that with the presence of endorsements in the industry, Nike, Titleist and Callaway benefit. This is not surprising since we have shown in our demand estimation the positive and significant endorsement effects on these brands. On the other hand, we find that the rest of the market suffers in market share due to endorsements. It is interesting to note that, the endorsement effect not only increases the share for the company with effective endorsers, but the presence of endorsements in the golf market increase the overall demand. Recall that the outside option in our model is "no purchase" and through our counterfactual we observe that the size of the outside option share decreases with the introduction of endorsements in the industry. This suggests that the endorsement effect is large enough such that those who would have otherwise not purchased a product do so when there are celebrity endorsements in the industry. This counterfactual not only makes clear that indeed endorsement effects are large enough to create product differentiation and shift market shares within the market but also is characterized as having a "primary demand" component where it attract customers who would have otherwise not purchased a product in the absence of celebrity endorsements.

2.6.2 Economic Value of Celebrity Endorsements

Having found that celebrity endorsements can change the utility a consumer obtains from consuming a product, we assess the economic value of a celebrity endorsement by looking at Tiger Woods. Our demand estimates suggest that Tiger Woods had a significantly positive effect on Nike products during the endorsement period. Given this finding, we ask the following question: What would have been the share of Nike's products if Tiger Woods elected to forgo endorsing Nike for the past 10 years? In 2000, Tiger Woods reportedly signed a 5 year $100 million dollar renewal contract with Nike, agreeing to endorse both apparel and golf balls, a golf segment that Nike entered as recently as 1999. In 2005, he was reported to have signed a 5 year $100 million extension. We would like to assess whether Tiger Woods' endorsement translated into sales and whether such sizable contracts were profitable. Therefore, in this section, by focusing on the impact of Tiger Woods on the Nike ball brand we run the counterfactuals to measure the economic value of a celebrity endorsement.

To find the impact of Tiger Woods on Nike's sales, we calculate the new market share of Nike's product under the environment where consumers choose a product without the extra "utility" associated with Nike products. To do so, we make the assumption that Tiger Woods would have continued his endorsement with the Titleist golf ball if it was not for Nike's offer in 2000. Therefore, we run the counterfactual by "assuming" that the statistically significant values of the "Tiger effects" are absent in the consumer utility for Nike products while the extra utility that was shown to be statistically significant for Titleist between 1997 to 2000 be present for 2000-2010. By doing this, we study the consumer's choice of Nike and its impact on sales under the "Tiger-less" environment.

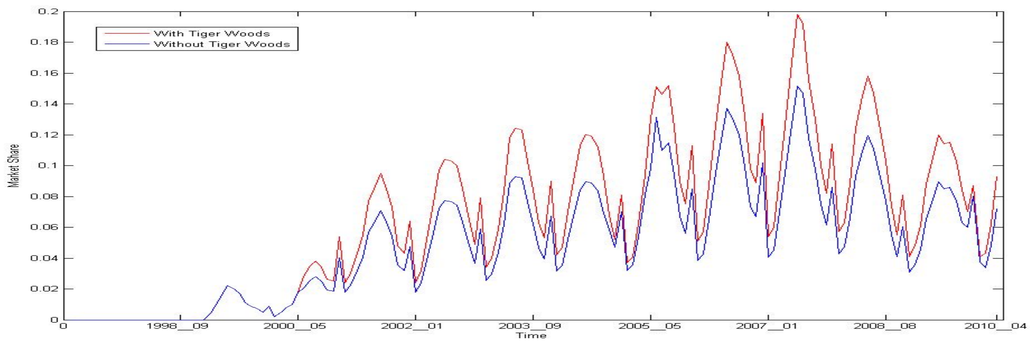

Figure 2.8: Share of the Nike Products for On & Off Course Shops Combined

Above are the aggregated market shares for Nike golf balls for all time periods for both on and off course combined. We can readily see that the market share is larger during the time that Tiger Woods was under Nike sponsorship. What this suggests is that for some consumers, the endorsement effect is large enough that they switch their brand choice.

Having shown that there is a general increase in the market share for Nike products over the time when Tiger Woods was under Nike's endorsement, we like to calculate the economic impact for Nike in terms of additional revenue, profit and customer acquisition. Assuming a pure strategy Nash-Bertrand equilibrium, we allow the firms to adjust their price setting behavior according to the environment. For example, it is reasonable to think that Nike takes Tiger Woods' endorsement into account before setting prices. For Nike, with Tiger Woods, we would expect that they would command a price premium given the additional utility attached to their products. In fact, other firms will also take this information into account before setting prices. For non Nike products, to compete against Nike, we expect lower prices. Specifically, in our scenario where we set Nike to be “Tiger-less”, we expect Nike would set their prices lower than in the regime with Tiger. For Titleist, since we assume that Tiger would have stayed with the company if it was not for Nike's multi-million dollar contract, we expect the price for Titleist products to be higher. In sum, depending on the market environment, we allow for the price vector to adjust so that it satisfies the first order condition of the profit function for each firms.

	Tiger with Nike	Tiger with Titleist	Difference
Average Price of Titleist	$25.79	$26.45	$0.66
Average Price of Nike	$17.27	$17.21	-$0.07
Other	$15.63	$15.87	$0.25

Table 2.12: Average Price Adjustments Before and After Policy

Empirically, we verify that in a "Tiger-less" environment for Nike, Nike adjusts its price accordingly by cutting prices. For Titleist, we observe that its price is adjusted upward in an environment where they did not lose Tiger Woods to Nike. For other firms, we see that when Tiger Woods was with Titleist, they were able to command a price premium of $0.25. Solving for the profit maximizing prices for two regimes, and with the estimated marginal cost we calculate the revenue, profit and customer acquisitions for the Nike company.

	Off course	On course	Both Retail
Revenue Gain	$90,158,776	$85,593,260	$175,752,036
Profit Gain	$61,125,284	$42,158,596	$103,283,880
Change in Sales	5,642,710	4,221,855	9,864,565

Table 2.13: Economic Value of Tiger Woods (2000-2010)

We find that during the endorsement period, Nike earned approximately $176 million in extra revenue from both on and off course combined. Furthermore, we estimate that the total additional profit earned by Nike's golf ball division was approximately $103 million for the ten year endorsement period. More importantly, for the Nike golf division, we find that the company acquired approximately 9.9 million additional sales during the endorsement period. We believe that, at least in the first half of the decade, this was pivotal for Nike as they were trying to launch their nascent golf division with the help of Tiger Woods as its primary endorser.[22] Through the endorsement of Tiger Woods, Nike was able to induce a significant portion of the population to switch their golf ball as a result of extra utility attached to Nike golf balls.

Recall that Tiger Woods signed two 5 year $100 million contracts. Therefore, given that he was paid a total of $200 million ($181 million in 1997 prices) for ten years, our estimates show that, just in golf ball sales in the United States alone, approximately 57% of its investment on endorsement was recovered by Nike. Given that the sport of golf is also widely popular outside the United

States, we conjecture that Nike would have recovered the majority, if not all, of its endorsement investment through golf ball sales alone. Considering the sales in the apparel and other equipments that Tiger Woods also endorsed as part of the contract agreement, we believe that Tiger Woods could have commanded an even larger contract from Nike.

2.6.3 Additional Counterfactuals

Negative Publicity

With the presence of a structural model we also are able to run simulations which looks at the impact of Tiger Woods' negative publicity on Nike orginiating from his martial infidelity. We, however, would like to note that the counterfactuals below are only loose estimates of the impact as the structural model does not identify the effect of Tiger Woods' scandal as cleanly as his endorsement effect. What our model is identifying with repect to the scandal variable is a variant of a pre and post effect. Now although we do we include time (year month interaction) fixed effect variable TD as well as firm specific time trend **F_tr** to control for any seasonality there could be a number of other time varying factors which could still bias our results. Therefore, we believe the below counterfactuals results should be viewed more skeptically than the ones above.

Things began to unravel for Mr. Woods at his Orlando area home on Thanksgiving night 2009. It was this night when he crashed his Cadillac SUV into a tree and fire hydrant after fleeing from an altercation from then wife Elin Nordegren. For the next few days rumors swirled that the altercation and accident were a result of Elin becoming aware of an affair Mr. Woods had with a New York city woman. With these rumors public more women began to emerge. By December 7, over a dozen women reported extramarital affairs with Tiger Woods and with this news Tiger Woods finally decided on December 11th to take an indefinite leave from the game of golf. After his December 11th decision, brands in which Tiger Woods had endorsement contracts with began to re-evaluate their positions with him. For instance, Gillette began to reduce its exposure of Tiger Woods on December 12th, Accenture eliminated Mr. Woods as an endorser on December 13th and Nike elected to publicly announce that it was standing by its celebrity endorser on December 14th. It was not until mid February that Tiger Woods re-emerged into the public life with a TV apology. However, he did not return to the game of golf until early April for the Masters golf tournament, missing the first three months of the tour season.

We address the question of what was the impact of Tiger Woods' scandal on Nike golf ball sales and profits for the six months following November 2009 with a counterfactual which assumes the scandal never occured. Additionally, to assess whether Nike's strategy to stand by Tiger Woods was the correct decision, in the next subsection, we run a second counterfactual which assumes the scandal occurs but Nike leaves Tiger Woods where he is without an endorsed brand.

With firms adjusting to their environment and setting prices accordingly, we expect that Nike would take into account the negative impact that Tiger Woods had on Nike products. Empirically, we find that without the scandal effect, Nike would have commanded a price premium of $0.25 For the non Nike products, it was negative 4 cents.

	Tiger with Scandal	Tiger without Scandal	Difference
Average Price of Nike	$11.84	$12.08	$0.25
Other	$14.48	$14.44	$-0.04

Table 2.14: Average Price Adjustments Before and After Policy

	Off course	On course	Both Retail
Revenue Gain	-$1,174,396	-$950,513	-$2,124,909
Profit Gain	-$947,138	-$518,936	-$1,466,074
Change in Sales	-79,890	-55,797	-135,687

Table 2.15: Economic Value of Scandal on Nike

Nonetheless, taking into account the price adjustments, we find that Nike lost approximately $2.2 million in revenue which we estimate to be a profit loss of $1.5 million. The number of sales lost due to the scandal is estimated at approximately 136,000. This suggests that without the negative publicity of Tiger Woods, Nike would have, ceteris paribus, earned $1.5 million more in profit.

Nike's Decision

We now assess Nike's decision to stand by Tiger Woods. To study Nike's decision, we run the counterfactual where Nike elects to terminate its ties with Tiger Woods. This is different from our first counterfactual where we assumed that Tiger Woods would have stayed with Titleist if it wasn't for Nike. In this counterfactual, we assume that Nike would have stayed with Tiger Woods until November 2009 and thereafter terminated its contract with Tiger where he would be without any endorsement. This is reasonable since we do not believe, post the scandal (November 2009 - April 2010) any company would have signed a contract with the golfer. We also assume that Nike do not sign any other top "celebrities" in place of Tiger Woods. This is natural as endorsement contracts in golf are characterized as multi-year contract where top players are tied to their endorsing company. In fact, in November of 2009, the "next best" player was Phil Mickelson and he was tied to the Callaway golf company.

While we have shown that the negative publicity of Tiger Woods generated relative loss in terms of revenue, profit and sales, our result (Model-Counterfactual) indicate that Nike would have lost even more had they ended its relationship with the golfer.

	Off course	**On course**	**Both Retail**
Revenue Gain	\$2,442,246	\$1,072,907	\$3,515,153
Profit Gain	\$2,124,528	\$547,060	\$2,671,588
Change in Sales	116,591	69,722	186,314

Table 2.16: Economic Value of Tiger Woods During the Scandal Period (12.09~04.10)

We find that Nike still benefited from the relationship with Tiger Woods despite the negative impact the scandal had on the company. During the time period of November 2009 to April 2010, had they ended its relationship with the golfer, Nike would have lost \$3.5 million of revenue or \$2.7 million in profit. From this, we conclude Nike's decision not to join the likes of Accenture, AT&T and Gatorade was the correct decision. Based on our finding, we find that even in the midst of the scandal Nike was actually better off with Tiger Woods than without.

2.7 Discussion and Conclusion

Our contribution to the marketing literature is twofold. First, we contribute to a topic that has been under-researched. To the best of our knowledge, we were able to identify only two studies that look at the economic value of celebrity endorsement. Even so, we believe that we are the first to study this domain by looking directly at the sales of the endorsed product. While it is terribly difficult to identify an endorser's effect on a firm's profit, we were able to do so in this paper. Second, not only is this topic under-researched, but it is an important topic that deserves the attention from marketing researchers. Over the past 30 years, celebrity endorsement has become an essential component of many firm's promotional strategy and is growing. As a result of this, we have seen a surge in both the number and the size of celebrity endorsement contracts. Given the increasing importance and presence of celebrity endorsements, we believe this topic is timely and relevant for researchers to study.

Our paper is not without any limitations. In regards to data, as discussed, we had data limitation issue where we were not able to include the "planned" advertisement level spending in our model. While we were able to make the case that excluding this variable would not create endogeneity bias, where the error terms is correlated with the endorsement variable, in an ideal setting we would include this variable in our full estimation.

In our counterfactual section, we ran a series of interesting policy simulations and were able to quantify the economic value of a celebrity endorsement in the context of Tiger Woods. We did this by "turning off" the endorsement effect in the consumer utility and comparing the before and after profit of the firm of our interest, Nike. In this regard, we are essentially studying a scenario where there is no consumer "inertia" or "stickiness" of celebrity endorsement effect. One may argue that when Tiger Woods switched from Titleist brand to the Nike brand, some consumer may have still attached the endorsement effect that Tiger Woods has had on Titleist to be present although this would have eventually died out as Tiger Woods continued to endorse Nike products. Therefore, one may look at our counterfactual as an upper bound of the economic value of celebrity endorsement. For the last counterfactual on Nike decision's to stand by the golfer, the direction is uncertain. This is because, if we believe that there is some residual value of endorsement effect that is present even after the early termination of the contract, one may argue that this is also an upper bound of their decision. But likewise, the negative scandal effect may not completely "shut off" after Nike's decision to terminate its contract with the golfer. Therefore, in this case, the direction is ambiguous.

Our study is in a static setting. We have two main reasons for this. First, we consider golf balls as "non durable" goods. We are comfortable with this as we do not believe that consumers make intertemporal tradeoff when purchasing golf balls. Not only do golf ball purchases take up small portion of a consumer's budget, but historically there has been no large fluctuation in price over time. Secondly, and most importantly, we do not believe that studying this in a static setting takes away our main insight and contribution in the marketing literature on quantifying the economic value of celebrity endorsements. What we find is that even though Tiger Woods was paid an exorbitant amount of $200 million for ten years by Nike, the endorsement fee was well justified. In golf ball sales in the United States alone, we quantify the endorsement effect on profit and find that approximately 57% of its endorsement investment was recovered. Taking into account the worldwide sales of golf balls and the sales in the apparel and other equipments that Tiger Woods also endorsed as part of the contract agreement, we believe that Tiger Woods' exorbitant $200 million dollar contract was actually not that large. In fact, we believe that he could have commanded an even larger contract from Nike.

For future directions, although our study has been on the economic value of celebrity endorsements in the context of Tiger Woods and the golf ball market, the implication of the endorsement effect extends to many other industries. While our study has looked into an endorsed product that is physically used in the profession by the endorser, it would be interesting to see how the endorsement effect changes for a brand that is not explicitly used by endorser in his profession. This would provide some insights of why firms like AT&T and Accenture ended its tie with the golfer.

Historically, celebrity endorsements have been an accepted strategy by many executives and have been around for centuries. Recently with the size of endorsements reaching the heights of tens to hundreds of millions of dollar it left us wondering of the effectiveness of these endorsements. In this paper, by taking a direct approach and studying the endorsement period in conjunction to the sales of the endorsed product we have shed some light on the economic value of celebrity endorsements. By studying the golf ball market we found that after controlling for the brand level exposure and the inherent quality of the endorser, there is a significant endorsement effect as a result of the extra utility attached to the endorsed brand. We empirically showed that endorsements can have a strong effect on consumer utility such that there is a shift in market share in the industry. In fact, we observe that endorsements have a dual component where existing customers switch to the more effective endorsed brand (business stealing) while bringing in additional sales from the outside (primary demand), which would have otherwise not occurred if it was not for the endorsement. However, managers must also be cognizant that, unlike the typical advertisement strategy, in celebrity endorsements there exist a negative component which can bring losses to the company. For Tiger Woods, we observed that while there was an overall positive endorsement effect, the negative publicity hurt Nike in profit and sales. What differentiates celebrity endorsements from other forms of promotion strategy is the natural evolution of the endorser over time which firms must take into account before making the decision to sign an extended contract with an endorser.

Chapter 3

Framing Effect and Consumers' Propensity to Save: Evidence from Merchant Rebate Program in Singapore[1]

"How do people spontaneously frame options they face in the world?"

Richard Thaler et al (1990)[23]

Using field data, our primary goal in this paper is to answer the question posed by Richard Thaler et al above. We take advantage of unique features of a rebate program to first determine that consumer choice departs from the normative prescription of economic theory. We then use the data to empirically identify how consumers spontaneously frame reward options they are faced with.

We argue that understanding how consumers frame options has large implications, directly lending insight into how card companies should design joint marketing activities that involve different merchants. To increase redemption activity, we propose that the card company should partner up with merchants that are both small and large in transaction sizes if the framing is "losses". On the other hand, if the framing is "gains", the network should compose of merchants with high transaction sizes.

[1]We thank the bank that provided the data and their tremendous help in making this research possible. We refrain from naming the individuals to protect the identity of the data provider.

We find evidence that consumers frame the rebate in terms of "losses". We examine and demonstrate that consumers not only wait for the optimal time to redeem, where redemption coincides with larger percentage off than previous opportunities, but they also put significant effort to amass rebates on a single card. Since consumers are unable to consolidate accrued rebates across cards, we investigate the extent to which consumers use the same card to amass rebates and its negative impact on card level benefits.

Our empirical analysis hinges on the variation in time in which the rebates were rolled out and the variation of consumer behavior in both the participating and non-participating rebate merchants. The richness of the data enables us to identify consumers' overall change in consumption behavior after the rebate program is introduced.

The paper is organized as follows: First, to motivate our empirical study, we provide a brief background in section 3.1 before providing an overview of the data with preliminary analysis in section 3.2. In section 3.3, we present a theoretical framework while in section 3.4 we introduce empirical analysis. In section 3.5, we conclude with discussion and directions for future research.

3.1 Background Information

3.1.1 Merchant Level Rebate Program

In this section, we describe the rebate program. To protect the identity of the bank, we make a deliberate effort to highlight only the major differences from traditional rebate programs that the reader may be familiar with. As it will be made clear in the next section, the features described here will enable us to answer the questions we set out to answer.

Starting in early 2010[2], the bank started to implement a merchant network rebate program. The program differs from other rebate program in that it is a common rebates program for its entire credit card platform, offering the same rebate benefits for all card holders above and beyond the benefit that each card gives, as long as transactions are made at the designated (participating) merchants.

[2]Exact date is not revealed to protect the identity of the bank

The rebate redemption is “instant” in that it can be redeemed in the very next transaction in participating merchants to offset the total cost incurred on the card. In each transaction, the cashier would explicitly ask whether or not one would like to redeem the previously accumulated dollar amounts. At that point, the consumer may decide to redeem or save the accumulated amounts for future use. After each transaction, the balance of rewards is clearly indicated on the receipt of the transaction.

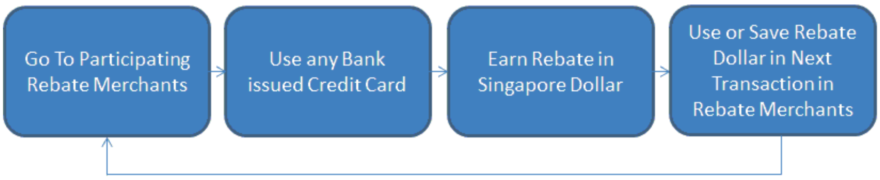

Figure 3.1: How Rebates Work

There is no expiration date for the amount accumulated and the program is available all year long on day-to-day purchases at over 500 outlets in Singapore with no limit to accumulation. Despite the fact that the rebate program is offered to all cards from the bank, it restricts consumers that hold more than 1 bank credit card from consolidating the accumulated amount across cards. We return to this restriction and its implication in later sections.

The type of participating merchants are, groceries, health/beauty, food/beverages, retail and entertainment/leisure with each merchant offering different percent off for the rebate. The percent off ranges from 1% to 10%, uniformly, at the merchant level. For example, if a particular restaurant chain is part of the rebate program, then the rebate percentage off would be uniform across participating branches in Singapore.

While the percentage off is identical across merchants, the availability of the rebate at different branches differed during 2010-2011, as the program was rolled out gradually,[3]

[3]We include a subset of the roll out months to illustrate the variation in rollout while protecting the sensitive data from the data provider

Month Since Rebate Introduction	% of merchant Roll out
1	48.20%
4	4.40%
8	3.60%
11	13.60%
12	1.00%
14	7.80%

Table 3.1: Percentage of new merchants in the rebate program each month since introduction

As we will return later, this variation in the roll out timing for a given merchant will help us in identifying the rebate effect on consumer behavior.

3.1.2 Normative Prescription of Economic theory

Having described the nature of the program, we now discuss the implications of the program and how we can expect consumers to change their purchase behavior. What is clear is that many consumers should switch from cash to bank credit card at the participating rebate merchants. This is because consumers will now be able to get additional money back from the program if they use their credit cards. We can also expect consumers with a different bank's credit card to switch over as long as the benefit of the rebate program outweighs the benefit that the competing card company gives to a card holder.

Conditional on switching to the bank card, however, it only makes sense to use the best card that provides the largest return. This is because, whatever card a consumer chooses, he/she will enjoy the same bank rebate benefits.

To make this clear, suppose that a consumer holds 2 cards, cards A and B.[4] While both cards are categorized as "Cash Rebate" cards, the two cards carry different benefits. Some of the perks of card A are that it gives up to a 5% rebate on grocery and coffee where the accrued rebate can be redeemed for store vouchers. On the other hand card B enables one to earn a 10% rebate all year round at the card B affiliated stores.

Suppose that a consumer holding the above two cards decides to go to Coffeeshop R, a participating merchant of the bank rebate program where all bank cards qualify for the 10% bank Rebate. In this case, the consumer should choose card A rather than card B. This is because, as mentioned above, card A itself has its

[4]Our intention is to not use the name of the card offered by the bank to keep it anonymous.

own benefit where using the card at a coffee shop entails a 5% rebate at the card level. Generally, because the rebate program is offered above and beyond the existing card level benefits, if a consumer carries multiple cards from the bank, the strategy in the participating rebate merchant should be to ignore the rebate program and use the best card that gives greatest card level benefit.

Once rebates are earned, even though the program permits the accumulation of rebates over time, the normative prescription of economic theory tells us that there is no reason to do so. This is because when rebates are earned in dollars, there is no financial "gain" from waiting as the total dollar amount received will be equal, regardless of when the redemption take places. In fact, if consumers take into account the time value of money since the accrued amount is not interest bearing, rational consumers should redeem the accrued amount as soon as it is made available.[5]

3.2 Data and Descriptive Evidence

We have three sets of data which we utilize to answer our questions. The first is the record of card transactions between April 2009 to August 2011 of a subsample of customers. This data consists of over 1 million observations, with corresponding information such as the date of transaction, customer number, card number, merchant number, amount spent, merchant type.

The second data is the rebate data consisting of subsample of customers' rebate redemption behavior from March 2010 to August 2011. Similar to the transaction data, corresponding information such as the date of transaction, customer number, card number, merchant number, amount spent, amount deducted are recorded. Within the rebate data, we took out anomalies such as transaction with missing gross amount (N/A) or negative transactions (signifying return of product).

The last data we have is demographics data that contains information such as age group, marital status, number of dependents, gender, occupation code, life style, postal code and income band.

[5]One would contend that consumers may randomly decide to redeem even though they are reminded in each transactions. However, as we will show, we argue that consumers are systematically saving and redeeming their rebate dollars. Redemption is done seamlessly where cashier would remind customer of the balance of rebate amount on the card and whether customer wants to redeem it. Therefore, as we will argue it is not the transaction cost that prevents consumers from saving.

For the purpose of answering our question, we created two sets of transaction data. The first is the data that contains about 500 merchants that participate in the rebate program. The second data set consists of transactions in non rebate participating merchant by the customers who made at least one transaction in one of the network rebate merchants. We set this aside to use it as part of the falsification test.

We have approximately 2,000 unique customers holding at least 2 cards with the bank. In terms of the amount of transaction activity in both data sets, the second data set is approximately 16 times larger given that the number of merchants involved is larger by almost an order of magnitude.

3.2.1 Transactions in Participating Merchants

Using the first data set, we look at the transaction behavior before and after the rebate program is introduced.

	Change from Before Rebate
Average No. of transaction in each merchants	+602.08%
Average Per Transaction Size	+31.47%
No. of Unique Transaction Cards	+346.26%
No. of Unique Customers	+243.88%

Table 3.2: Summary statistics of transaction before and after the rebate kicks in about 500 rebate merchants (April 2009-August 2011)

As made evident above, we find that the average number of transaction in each merchants increases dramatically. This increase is expected since consumers can earn additional bonus through the 1%-10% instant rebate. The mean transaction size also shows an increase which suggests that perhaps consumers are spending more because of the rebate.

The unique number of card transaction and the unique customers that take advantage of the program increases dramatically. While there is a dramatic increase in both unique transaction cards and unique customers, we are not able to identify if this increase is coming from consumers purchasing more or simply substituting away from another bank card or from cash. We can only determine this if we are able to obtain merchant level transactions before and after rebate is introduced. Regardless of whether the increase is coming from a primary demand effect or substitution effect, thus far, the transaction behavior abides with what we had predicted in section 3.1.2.

3.2.2 Rebate Redemption Behavior

During the rebate period, how are consumers behaving with accumulated rebate dollars? We take the redemption data that looks at the amassing and redeeming behavior.[6]

	Card Level Average
Redemption Frequency	60%-80%

Table 3.3: Summary statistics of card level redemption

We find that available rebates are redeemed on average 60-80% of the time. In other words, when a customer makes a transaction and given that they have an outstanding balance of rebates accrued from previous transactions, only 6-8 out of 10 times are consumers redeeming the rebate. This is puzzling because as mentioned in section 3.1.2, if consumers view the rebate dollar purely as a financial bonus, they should not wait and accumulate the redemption. This is because there is no financial benefit to how much the consumer will ultimately bring in through the rebate bonus (because the amount accumulated is not interest-bearing).

Then the question is, why not redeem every period? We discuss why we may be observing this consumer behavior. There are a few competing reasons readers may find it plausible. These are

1. Transaction cost to redeem is high / time to redeem is costly
2. Consumers are not aware of rebate
3. If redeem, the redeemed portion does not qualify for the "rebate %"
4. Consumer may be randomly redeeming it for no particular reason.

However, reasons number 1 and 2 are not likely because our institutional knowledge tells us that the cashier reminds them each transaction and the additional time that it takes to redeem is virtually non existent. The third potential explanation cannot be the reason because the longer one waits, the larger the portion that will not qualify for the rebate. Lastly, it is plausible that consumers are

[6] Since the rebate program was a card based program where consumers can only accumulate rebate at the card level and cannot consolidate across cards,we will look at the redemption behavior at the card level in this section. The exact redemption frequency is masked with the request from the data provider.

randomly redeeming with no particular reason. However, as we will show empirically, redemption does not seem to be driven purely at random.

We postulate that consumers may decide to postpone redeeming rebate because,

1. The amount of "gain" on the account is too small to give sufficiently positive utility.
2. The redemption looms "larger" on different occassions.

To find evidence for this, we look at the time in which redemption did not take place.

	Redemption vs Non Redemption : mean [min median,max]	sig?
$ redemption	+26.56% [+325.00%,+36.84%,+115.30%]	yes
% off from total sales	+53.92%[+700.00%,+60.31%,+75.70%]	yes

Table 3.4: Redeemed vs Non Redeemed Periods

As shown above, during the actual redemption period, the $ amount redeemed is 26.56% larger than the amount the customer would have earned had there been a redemption during the non redeemed periods.[7] Similarly, the total discount one obtained in the redemption period is 53.92% higher than in the scenario that the consumer redeemed in non redemption periods. In both cases, it is clear that consumers are saving up their rebate amounts for future uses in order for it to give them a "larger" return.

3.3 Theoretical Framework

In this section, we discuss more formally why consumers may be delaying their redemption with the theoretical underpinning of the prospect theory. In prospect theory, Kahneman and Tversky describe two phases in the choice process. These are the early phase of editing followed by the evaluation phase.[24]

The editing phase organizes and reformulates an option that one has in order to simplify the evaluation process. They note that the editing process is what drives many anomalies of preferences. However, they focus on the choice problem (evaluation) and proceed their analysis stating that it is reasonable to assume that the original formulation of prospect is either left with no possibility

[7]This by definition has to be true because rebate amount is carried over.

of further editing (simplification) or if editing is possible, there is no ambiguity to the researchers.[8][24]

Outside of experimental settings, achieving unambiguous edits are difficult. Because the outcome is sensitive to and susceptible to editing, the theory often falls short of its full potential. Our goal is to identify what editing/framing is at work given the choices made by the consumers.

"Peanuts Effect"

To describe our data, we take the variant of the value function of the prospect theory known as the "Peanuts Effect".[25, 26]The key difference between the traditional value function of the prospect theory and the peanuts effect is that, in the peanuts effect value function, there are three inflection points as oppose to one, as shown below. Essentially, the region between the vertical dotted lines reverses the prediction of the prospect theory where small gains (losses) do not necessarily translate to the greatest marginal utility (disutility), resulting in risk taking (averse) behavior rather than risk averse (seeking) behavior.

In the previous section, we stated that consumers may not be redeeming because,

1. The amount of "gain" on the account is too small to give sufficiently positive utility.
2. The redemption looms "larger" on different occassions.

The shape of the value function below can explain both statements, depending on how consumers frame the rebate. In our setting, the y axis is the value or utility one obtains when redemption takes place while the x-axis is the dollar amount earned through rebate.

As stated above, the consumer may not be redeeming because the dollar amount is not sufficiently large. In this case, the redemption may be postponed given its size. For example, a typical consumer would care less if they received $0.02 bonus on a purchase. If this is the case, consumers would wait until they have amassed a sufficient dollar amount on their rebate account and redeem it as soon as the "threshold" (y) is reached, as a result of diminishing marginal utility

[8] Kahneman and Tversky states "In this paper, we discuss choice problems where it is reasonable to assume either that the original formulation of the prospects leaves no room for further editing, or that the edited prospects can be specified without ambiguity"

in the value function. This would support our observation of a larger absolute redemption of +26.56% in table 3.4.

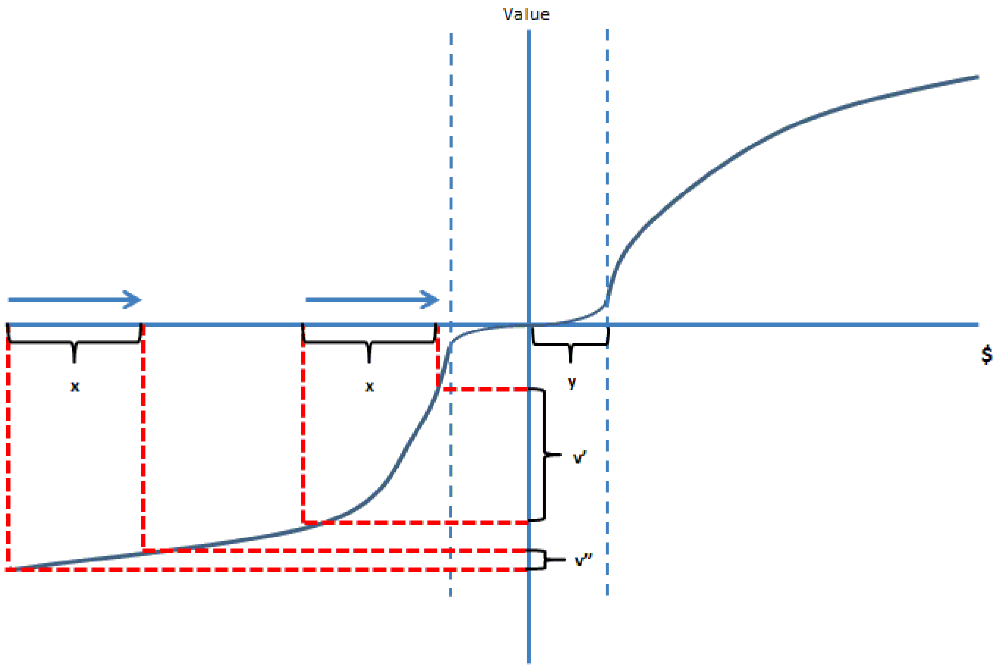

Figure 3.2: Consumer's propensity to wait redemption

On the other hand, if the determinant of the decision process is from the relative "gain" from each transaction, there are two ways in which the option can be edited. The consumer can frame the discount as "gain from losses" thus being on the third quadrant of the value function above. A $3 off from a $6 transaction looms larger than a $3 off from a $60 transaction where x would be $3 in this example. (v" vs v') This is consistent with the observation on table 3.4 as consumers would wait until the redemption is worthwhile (significant % off).

Alternatively, one can argue that consumers edit the discount as gains with the x axis being "% discount". The argument would be that consumers may be waiting for a threshold of discount that gives them sufficiently large positive utility, similar to the argument on the absolute dollar amount.

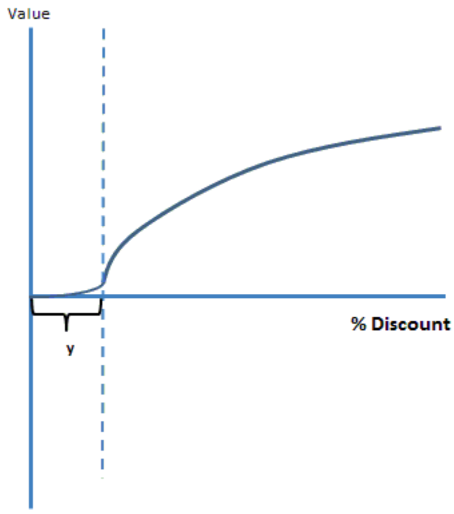

Figure 3.3: Framing discount as gains

Our goal is to empirically discern which is the dominant framing mechanism at play in this rebate program. Understanding this is important for marketers because knowing this they can better understand consumers' decision process which in turn will enable them to better design the rebate program.

3.3.1 Empirical Strategy

We first go about disentangling the two possible explanations (absolute dollar or percent off from a transaction) by taking advantage of the variation of both the redeemed dollar amount and the amount spent in a given transaction.

If consumers are framing this as pure gains from rebate dollars, we should observe that a consumer's propensity to redeem is based purely on the dollar amount saved on the card. However, if consumers are framing the process as a "discount" and thus optimizing the timing of redemption, we should see variation in the redemption pattern as a function of the transaction size, keeping the redemption dollar amount constant.

As shown below, for the first case (pure dollar gain), we should expect the relationship between transaction and redemption amount to be independent, whereas in the second case (discount), we should observe positive dependencies.

We note that we are able to discern this empirically because the feature of the program is such that consumers willingly choose when to redeem their rebate amount and there is no limit and expiration date of rebate accumulation.

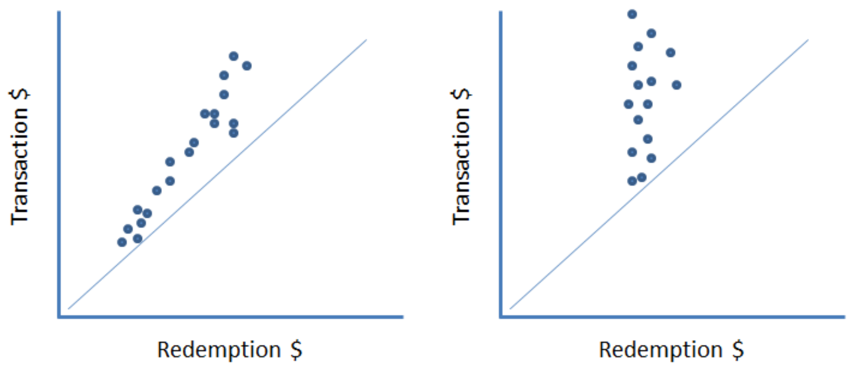

Figure 3.4: Expected Redemption Pattern for % off and absolute $ respectively

To find out which of the two explanations are driving consumers' propensities to wait to redeem, we plotted the transaction versus redemption variables and it was unclear what mechanism was at work.[9] In the following section, we identify which mechanism is at play in a more systematic way.

Framing the Discounts

If we find that consumers are redeeming with regards to absolute amount of dollar earned, then we can conclude that consumers are on the 1st quadrant of the value function on figure 3.2. However, as mentioned above, if consumers are redeeming it based on the relative gain from each transaction (discount), both quadrants can explain the behavior, depending on the label of the x-axis. We now discuss how we will discern which framing is at work.

In order to identify whether consumers are viewing the discount as "gains from losses" from a dollar perspective or purely as "gains" from a percent off perspective we take advantage of the shape of the value function.

If the percent off is viewed as "gains" as shown in figure 3.3, conditional on having reached the inflection point, the value function tells us that as the % off increases, the marginal utility decreases. The concavity of the value function therefore tells us that consumers would be more likely to redeem as soon as the inflection point is reached. (segregate gains) In other words, keeping the accrued rebate dollar constant, the smaller the transaction size (larger % off) , we would expect the redemption to be less likely.

If the percent off is viewed as "gains from losses" in terms of dollar amount as shown in the 3rd quadrant of figure 3.2, then the convexity of the value function

[9]We do not share the plot due to data release agreement.

on the left side of the inflection point would tell us that for a given accrued rebate amount, the propensity of redemption increases as the transaction size decreases. This is because the the marginal utility increases as we approach the inflection point.[10]

The two value functions predict different directions on the propensity to redeem based on the change in transaction size. Therefore, we will be able to discern whether consumers are on the 3rd quadrant of the value function in figure 3.2 or 1st quadrant in figure 3.3.[11]

3.4 Empirical Analysis

Based on our descriptive findings, our goals in this section are twofold. The first is to identify which mechanism is in play during redemption given our finding that consumers are not redeeming the rebate immediately. If the redemption is driven by percent off, we want to identify how consumers frame the discount. Our second goal is to understand the impact of the rebate program on consumers' overall card usage. Mainly, we want to understand the impact of framing and how the rebate had a significant impact in altering the choice behavior across cards with those with more than one bank credit card.

3.4.1 Redemption Behavior

As mentioned, if the rebate is framed as pure dollar gain, we should expect the amount spent to be independent of the amount redeemed. However, if it is framed as gain from losses, the timing of redemption should be a function of amount spent. To discern this, we run the following regression,

$$\begin{aligned} Redemption_{i_cjt} &= \beta_0 + \beta_1 RebAcc_{i_ct} + \beta_2 PercentOff_{i_ct} + \sum_{t=3}^{14} \beta_t Month_t \\ &\quad + \sum_{j=15}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i + \epsilon_{ijt} \end{aligned}$$

[10]Or the marginal disutility decreases as the transaction size increases (larger losses)

[11]Alternatively, prior work has shown that consumers' propensity to spend increases if framed as "gains". Therefore, one way to look at this is to look at what consumers "spend" on the additional money they receive through the program. However, we are not able to identify the particular type of products purchased when redemption takes place. We only have a total transaction size from a shopping trip.

$Redemption_{icjt}$ is a binary variable of 1 if consumer i decides to redeem card c at time t at merchant j. $RebAcc_{ict}$ is the amount of dollar accrued by consumer i in card c at time t. $PercentOff_{ict}$ is the percentage off a consumer i would get from using card c for transaction at time t. Therefore $PercentOff_{ict}$ is $\frac{RebAcc_{ict}}{Transaction_{ict}}$ where $Transaction_{ict}$ is the transaction size of consumer i using card c at time t. These two variables will allow us to determine whether or not consumers are viewing the rebate in terms of absolute gain in dollars or relative gain in terms of discounts.

We include controls such as the month dummy for seasonality, the merchant fixed effects and customer fixed effect. We include merchant fixed effect to control for any unobservable merchant level characteristics that may impact redemption. We also include customer fixed effect to control for any variation of redemption pattern that can be explained by customer specific characteristics.

Our coefficient of interests are β_1 and β_2. The coefficientβ_1 is identified from the variation of the absolute rebate amount that explains the variation in the redemption behavior keeping the relative discount constant. In other words, if \$2.50 is redeemed and \$1.50 is not when \$5.00 and \$3.00 are spent respectively (both 50% off), then consumer redemption behavior must be driven by the framing of the rebate as purely dollar gain. In this particular case, the "limen" would lie anywhere between \$1.50 and \$2.50.

Similarly, the identification of β_2 comes from the variation in relative discount that explains the redemption behavior keeping absolute rebate amount constant. For example, if a \$2.50 rebate on a \$5.00 transaction is redeemed while a \$2.50 rebate on a \$20.00 transaction is not, then consumers' propensity to redeem must come from the relative "% off" from the total transaction.

When we run the logit regression, we find evidence that consumers' decisions are driven by framing the program as "discounts". We find the estimate of the β_2 to be 3.821 while for β_1 it is not significant at the 95% level. We run both the linear probability model as well as the logit model and include it in the appendix.

	Logit		
	Estimate	Std Error	z-value
Intercept	-15.320	5690	-0.003
Rebate Accumulated	**-0.008**	**0.005**	**-1.839**
Potential % off	**3.821**	**0.199**	**19.231**
Month D	yes	yes	yes
Merchant Number D	yes	yes	yes
Customer Number D	yes	yes	yes

Table 3.5: Redemption

This result makes clear that the redemption probability increases with the increase in the relative amount that one "gains" from the purchase (discount) rather than the absolute dollar amount of the rebate. In other words, conditional on a purchase of a product, redemption occurs more frequently if the accrued rebate is as large as the transaction size. Based on this model, we calculate the predicted redemption probability if the potential percent off were increased in the data.

Additional % off	Difference
10	0.06
20	0.11
40	0.19
50	0.23
90	0.31
100	0.32

Table 3.6: Differences in Predicted Redemption Probability

The larger the amount of discount one receives, the probability of redemption increases. The difference can be as large as 32% as shown above.

Are Discounts Framed as Gains or Losses?

As mentioned in the empirical strategy section, having found that redemption is driven by discounts rather than by the absolute dollar amount accrued, we need to discern whether consumers are framing this as "gain from losses" or "gains of discount".

We argued that if the percent off is viewed as "gains" as shown in figure 3.3, where the value function is a function of "% off", the concavity of the function tells us that redemption will decrease as transaction size decreases keeping accumulated rebate constant. (redemption decreases as % off increases) On the other hand, if consumers frame the discount as "gains from losses" as shown in figure 3.2, the convexity of the function tells us that the propensity of redemption would increase as the transaction size decreases. Based on the change in transaction size, with the two value functions predicting different directions on the redemption pattern, we run the following regression,

$$\begin{aligned} Redemption_{i_c jt} &= \beta_0 + \beta_1 RebAcc_{i_c t} + \beta_2 Transaction_{i_c t} + \sum_{t=3}^{14} \beta_t Month_t \\ &+ \sum_{j=15}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i + \epsilon_{ijt} \end{aligned}$$

Keeping the rebate amount accrued constant, we expect that increase in transaction size would increase redemption in "gains" scenario, whereas the opposite would occur in the "gains from loss" scenario. Therefore, our variable of interest is β_2 where if it is negative, it tells us that consumers are framing the discount as "gains from losses". If it is positive, it would suggest that it is framed as "gains" in % off. For the same reasons mentioned in the previous equation, we include controls such as the month dummy for seasonality, the merchant fixed effects and customer fixed effect.

	Logit		
	Estimate	Std Error	z-value
Intercept	0.071	0.962	0.733
Rebate Accumulated	0.048	0.004	11.851
Transaction ($ spent)	**-0.0014**	**0.0003**	**-5.338**
Month D	yes	yes	yes
Merchant Number D	yes	yes	yes
Customer Number D	yes	yes	yes

Table 3.7: Framed as Gain or Loss

We find that the β_2 is negative and statistically significant. This tells us that consumers' propensity to redeem decreases when transaction size increases suggesting that the discount is framed as "gains from losses" in dollar amount, or the 3rd quadrant of the value function in figure 3.2.

Implication

Our findings in this subsection tell us that there are two determinants of when a consumer would redeem, the current amount of rebate accrued and the contemporaneous transaction size. If consumers are redeeming when they are achieving highest utility, this tells us that to achieve this consumers can do two things.

First, a consumer can simply wait and time their redemption based on their transaction size. Mainly, a consumer may forgo to redeem and save the rebate dollar for later use if he/she expects that future transactions will give him an overall larger % off from the transaction. An example may be a consumer who shops in a grocery store with the total bill of $40, who forgoes redeeming $2 of rebate because he/she knows tomorrow he/she will go to a rebate participating coffee shop that will cost only $4 giving a 50% discount from a transaction. We have already shown that consumers are indeed timing their decision based on the amount of transaction that takes place. This is because after controlling for the rebate size, we were able to show that variation in transaction size captures the variation in redemption behavior.

Second, a consumer can put extra effort to amass as much rebate dollar as possible. To do this, consumer can increase the usage of the bank card in the network of rebate merchants. We have found evidence for this increase in card usage. Conditional on increasing the usage, a consumer can accumulate rebate dollars more quickly if they used the same card. This is because even though all bank credit cards qualify for the same amount of rebate, the program restricts consolidation of rebates across cards. Thus, the only way to maximize accrual, conditional on the same number of transactions, is to use the same card.[12] We take advantage of this feature of the program to identify whether or not consumers put extra effort above and beyond simply timing their redemption.

3.4.2 Effort to Accrue Rebate

We noted that the first way that a consumer can increase utility is to amass as much rebate dollars as possible. Conditional on increasing the usage, a consumer can accumulate rebate dollars more quickly if they used the same card.

[12]This has large implication as we have mentioned there is a tradeoff between maximal accrual versus maximal benefit that a consumer can obtain based on card level benefit that differs across network of rebate merchants. We come back to this to see if indeed consumers are compromising the features of the card level benefits.

This is because even though all bank credit cards qualify for the same amount of rebate, the program restricts consolidation of rebates across cards.

To understand if this is occuring, we construct customer level consecutive card usage before and after the program. We surmise that if consumers are putting more effort to increase the accrual of rebate dollars, then we would see a significant increase in consecutive usage at the card level.

Since, consumers who hold only 1 card with the bank will, by default, use the same card over and over again, we restrict our sample to consumers with at least 2 cards.

To not bias the usage that can carry over from before the rebate time period, when calculating the cumulative usage, we reset customer transactions to 0 when the rebate kicks in and calculate the cumulative usage since the time when rebate is active in the merchant.

	Change from Before "Rebate"
Average Consecutive Usage Of Same Card	+138.27%

Table 3.8: Summary statistics of transaction before and after the rebate kicks in about 500 rebate merchants for each customers (April 2009-August 2011)

As shown above when we look at the before and after usage of this variable, there is an increase of 138.27%. To do a more systematic analysis and to control for potential confounds, we run the following regression,

$$
\begin{aligned}
CumulativeUsage_{iCjt} \;=\;& \beta_0 + \beta_1 RebateRollOut_{jt} + \beta_2 TransactionSize_{iCjt} + \beta_3 CardLevelRanking_{iCjt} \\
&+ \sum_{t=4}^{15} \beta_t Month_t + \sum_{j=16}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i \\
&+ \sum_{k=N+1}^{K} \beta_k (MerchNumber \times Month)_k + \epsilon_{ijt}
\end{aligned}
$$

$CumulativeUsage_{iCjt}$ is the cumulative usage of card c owned by consumer i at rebate merchant j at time t. As mentioned, to not bias the usage that can carry over from before rebate time periods, when calculating the cumulative usage, we reset customer transactions to 0 when the rebate kicks in.

Our variable of interest is β_1 where the $RebateRollOut_{jt}$ corresponds to 1 if merchant j is part of the rebate program at time t. We discuss how the parameter is identified in the next subsection. For controls, we include the transaction amount, card level ranking[13], month of the transaction, the merchant in which the transaction took place as well as a customer fixed effect.

We include the transaction amount that may impact overall usage at the card level. One can surmise that large purchases may impact the ability to use the same card given the credit limit. While our institutional knowledge tells us that consumers in this market do not usually spend their money up to their credit limit, if the credit limit is a factor in cumulative usage we would expect the sign to be negative.

We include the card level ranking that tells us the relative ranking of the card with respect to other cards that a customer currently carries. As mentioned, while the rebate program was universally applied to all cards, each card has its own benefits. We have the benefits in terms of relative rank order at each transaction where 1 signifies the greatest benefit in terms of dollar amount the card holder would receive in rewards. So in the case of card A and card B we used as an example, card A be coded 1 while card B would be coded 2 at Coffeeshop R. This is an important control since one can surmise that consumer may use the same card over and over again because it is the best card available to them. So if this factor is driving the cumulative usage, we would expect β_3 to be negative.

We also include month, merchant and customer fixed effects. The month fixed effect captures any increase or decrease in usage due to seasonal reasons while the merchant fixed effect captures any merchant level characteristics that may be driving the increase or decrease in the cumulative usage. We include a customer fixed effect to control for any variation that may come from consumers' propensity to use the same card. By including these controls, we are able to isolate out the impact of the rebate on cumulative usage.

Lastly, we include an interaction term that interacts merchants with month to capture any time varying merchant level promotion that may impact usage of the same card.

[13]Since we focus on consumers with more than 1 cards, for each transaction, we code the card level benefits in terms of ranking. For example, if a customer holds 3 cards with the bank, and a transaction is at a merchant j, we rank which card is best for that transaction. We expect that cumulative usage should be inversely correlated with the ranking (rank 1 being highest) if indeed consumers are optimizing at the card level. Keep in mind that regardless of the card level benefit, the rebates amount awarded are equal across all cards.

Cumulative Usage	(2)		
	Estimate	Std Error	t-value
Intercept	-2.322	8.930	-0.260
AfterRebateRoll	**6.187**	**0.335**	**18.477**
Transaction size	-0.001	0.001	-0.864
Rank of Card	-0.191	0.143	-1.336
Month D	yes	yes	yes
Merch Number D	yes	yes	yes
Custo Number D	yes	yes	yes
Month D x Merch number D	yes	yes	yes

Table 3.9: Effect of Rebate on Cumulative Card Usage

As shown above, we find that even after including controls, there is a significant positive impact of cumulative usage after the rebate kicks in. The result tells us that there is an approximate 6 additional consecutive usage of the card at the rebate merchants after rebate program is introduced.[14] This is a significant increase from the average number of customer level (across all cards) consecutive transactions.

While we have found evidence of more effort is being put in by consumers to accrue rebates, the above increase in consecutive usage has a competing explanation. As was observed in the descriptive section, there was a large increase in card usage in the participating merchants. Therefore, one can argue that we see an increase in consecutive usage simply by the fact that there was an overall increase in average number of transactions. In other words, because consumers are using the cards more often, all cards that he/she carries would now be more likely to be used more consecutively. To discern whether this usage increase is in fact due to consumers' propensity to save up rebates rather than simply from increase in overall usage, we run two regressions.

First, conditional on the rebate program being introduced, we attempt to explain the cumulative usage by the amount of rebate accumulated on each card. To do so, we merged rebate data with the transaction data. By merging these two data sets, we now have the transaction behavior as well as the contemporaneous amount of rebate accumulated on each card. The regression we run is,

[14]We include in the appendix model that progressively include controls.

$$
\begin{aligned}
CumulativeUsage_{i_c t \in AR} \quad = \quad & \beta_0 + \beta_1 RebAcc_{i_c t} + \beta_2 TransactionSize_{i_C jt} + \beta_3 CardLevelRanking_{i_C jt} + \\
& + \sum_{t=4}^{15} \beta_t Month_t + \sum_{j=16}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i \\
& + \sum_{k=N+1}^{K} \beta_k (MerchNumber \times Month)_k + \epsilon_{ijt}
\end{aligned}
$$

$CumulativeUsage_{i_c t \in AR}$ is the cumulative usage of customer i using card c at time t where t is after rebate (AR) is introduced. The variable of our interest is β_1 where we would expect it to be positive if indeed consumers' propensity to use the same card is impacted by the amount of rebate accumulated on each card. In other words, if consumers wants to quickly accumulate, then we would expect consumers to choose cards with higher rebate dollar accumulated.

	Estimate	Std Error	t-value
Intercept	4.167	17.480	0.238
Rebate Accumulated	**0.067**	**0.014**	**4.848**
Transaction size	0.001	0.001	0.905
Rank of Card	0.135	0.264	0.512
Month D	yes	yes	yes
Merch Number D	yes	yes	yes
Custo Number D	yes	yes	yes
Month D x Merch number D	yes	yes	yes

Table 3.10: Cumulative usage after the introduction of rebate program

As shown above, we find that amount of rebate accumulated on each card does have a positive and significant impact on cumulative usage of the card. The amount accumulated does describe the cumulative usage, where higher rebate in each cards is associated with consumers' propensity to use more of the same card. The result tells us that with all else being constant, when the accumulate rebate goes from 0 to $100, then the propensity to use the card consecutively increases by 6.7.[15]

The second way in which we discern whether this usage increase is in fact due to consumers' propensity to save up rebates rather than from an increase in usage, we truncate the data. For each customer, we truncate the data so that the number of transactions before and after the rebate programs are equal. We then

[15] It is interesting to see that the ranking of the card has no impact on the cumulative usage of the card.

run the same original specification that corresponds to table 3.9. By running this, we can control for potential impact of overall increase in transaction that may be impacting the overall increase in cumulative usage.

As we have observed previously, many transactions came after the rebate was introduced so there were not many customers who had transaction in merchants before the rebate program was rolled out. The balanced sample of before and after rebate consists of 900 transactions each. Keep in mind that this is a significant decrease in number of transactions and cards/customers.

	Estimate	Std Error	t-value
Intercept	3.841	4.440	0.865
AfterRebateRoll	**1.278**	**0.593**	**2.156**
Transaction size	-0.001	0.003	-0.359
Rank of Card	0.157	0.350	0.450
Month D	yes	yes	yes
Merch Number D	yes	yes	yes
Custo Number D	yes	yes	yes
Month D x Merch number D	yes	yes	yes

Table 3.11: Truncated Regression Results

By running the same specification on table 3.9, we find that the increase in consecutive usage of the card is not as large as we found previously but still positive and statistically significant. As shown above, the transaction of the same card by the customer increases on average 1.28 after taking into account all the fixed effects. While this number seems very small, this translates to approximately 46% increase after the rebate program is introduced in this subsample. Now, since we have truncated the data, it cannot be the case that the increase in cumulative usage is due to an increase in overall transactions. Coupled with table 3.10, we believe that increase in consecutive usage came from the rebate program where consumers' propensity to use single card increased to accrue rebate.

3.4.3 Identification

We ran three different regressions to show evidence that consumers are indeed intentionally using one card more frequently for the purpose of accruing rebate dollars. However, we did not elaborate on how the coefficient of $RebateRollOut_{jt}$

is identified. We discuss this here.[16]

$RebateRollOut_{jt}$ is a binary variable of 1 if merchant j is part of the rebate program at time t. We argue that we have sufficient variation to identify the impact of the rebate on consumer behavior, in this case, cumulative usage of the card.

The first source of identification is the time of roll out of the program. There are a total of about 500 merchants that become part of the network of rebate program after its introduction in early 2010. Out of the merchants that eventually join the network, only 48.2% joined the network on the first month the program was introduced. The rest of the merchants gradually rolled out in the next 15 months. [17]

This variation in roll out help us rule out alternative events that could have coincided with the rebate program. To better understand how the variation helps our identification strategy, imagine that all rebate merchants in Singapore became part of the rebate program in early 2010. If this was the case, the above analysis would suffer from serious confounds as the only source of variation comes from 1 event of early 2010.

In this particular case, it turns out that early 2010 is when Universal Studio Singapore at Resort World Sentosa and Marina Bay Sands which includes 963 hotel rooms, shopping mall and convention center opened for the first time. So had the bank rolled out the rebate uniformly across all about 500 stores at the same time, we would not be able to isolate the rebate effect from the events that surrounded this promotion.[18]

Our second source of identification is variation in consumer behavior across merchants, the set of merchants that participated and the set of merchants that did not participate in the rebate program. If indeed it is the rebate program that impacted consumers to put more effort to amass rebate and thus increased the propensity to use the same card more frequently, we would not expect this behavior to persist in non rebate participating merchants. In the next subsection, by looking at consumer behavior in the non participating rebate merchants we run a "falsification test". By artificially creating a day of "rebate" we will determine whether the same set of customers who have shown to be impacted above

[16]For the redemption behavior, the identification of the coefficient on absolute rebate amount and relative discount were mentioned within the subsection 5.1.

[17]In table 1, only partial months were tabulated for data protection reasons.

[18]Since the coefficient on $RebateRollOut_{jt}$ captures the average impact of cumulative usage after rebate kicks in, it may be true that one large spike in cumulative usage could have driven a statistically significant mean effect. To guard against this confound, we run a robustness check in the next section that rules out this concern.

have the same behavioral change in nonparticipating merchants.

3.4.4 Robustness Check

Persistent Effect of Rebate Program on Cumulative Usage

We have shown that consumers are using the same card more frequently after the rebate is introduced. As we have specified the model, our coefficient on the $RebateRollOut_{jt}$ was binary where it "turns on" when rebate is introduced in merchant j. Therefore, the coefficient captures the average effect of rebate on consumers' propensity to use the same card. We mentioned that early 2010 was when there were events surrounding the promotion. It may be of a concern that this average effect that we capture is driven primarily by one or two large spikes in cumulative usage surrounding the events. To show that indeed the effects had a long persistent effect after the rebate is introduced, we run the following specification that separately identifies the $RebateRollOut_{jt}$, based on time since roll out.

$$\begin{aligned} CumulativeUsage_{ijt} \sim\ & \beta_0 + \beta_2 TransactionSize_{ijt} + \beta_3 CardLevelRanking_{it} \\ & + \sum_{s=4}^{21} \beta_s (RebateRollOut_{jt} \times TimeSinceRebateRoll_s) + \sum_{j=22}^{33} \beta_j Month_j + \sum_{k=34}^{M} \beta_k MerchNumber_k \\ & + \sum_{L=M+1}^{N} \beta_L CustomerNumber_L + \sum_{k=N+1}^{K} \beta_m (MerchNumber \times Month)_m + \epsilon_{ijt} \end{aligned}$$

The variables of interest are the coefficient on $RebateRollOut_{jt} \times TimeSinceRebateRoll_s$ where $TimeSinceRebateRoll_s$ is 1 if time since (in month) rebate is introduced is s.

We find below that there was a persistent effect of rebate impact the cumulative usage of the card after the rebate began.[19] This gives us more convincing evidence that the policy had a persistent change in consumer behavior rather than being a one time shock that may have been due to unobservable surrounding events.

[19]We mask the actual estimate by inflating/deflating both the parameter estimates and the standard errors.

	Estimate	Std Error	t-value
Intercept	0.315	1.632	0.193
Transaction Size	0.000	0.000	-1.000
Card Level ranking	-0.048	0.026	-1.847
AfterRebateRoll x Time Since Rebate (0 month)	-0.034	0.411	-0.083
AfterRebateRoll x Time Since Rebate (1 month)	0.461	0.372	1.238
AfterRebateRoll x Time Since Rebate (2 months)	**1.275**	**0.433**	**2.944**
AfterRebateRoll x Time Since Rebate (3 months)	**0.675**	**0.250**	**2.702**
AfterRebateRoll x Time Since Rebate (4 months)	**0.487**	**0.270**	**1.808**
AfterRebateRoll x Time Since Rebate (5 months).	**0.949**	**0.254**	**3.738**
AfterRebateRoll x Time Since Rebate (6 months)	**0.904**	**0.232**	**3.902**
AfterRebateRoll x Time Since Rebate (7 months)	0.205	0.302	0.679
AfterRebateRoll x Time Since Rebate (8 months)	0.593	0.336	1.766
AfterRebateRoll x Time Since Rebate (9 months)	**0.757**	**0.341**	**2.220**
AfterRebateRoll x Time Since Rebate (10 months)	**1.238**	**0.274**	**4.516**
AfterRebateRoll x Time Since Rebate (11 months)	**1.847**	**0.081**	**22.916**
.AfterRebateRoll x Time Since Rebate (12 months)	**1.988**	**0.414**	**4.804**
AfterRebateRoll x Time Since Rebate (13 months)	**2.284**	**0.377**	**6.062**
AfterRebateRoll x Time Since Rebate (14 months)	**2.836**	**0.438**	**6.478**
AfterRebateRoll x Time Since Rebate (15 months)	**2.344**	**0.257**	**9.121**
AfterRebateRoll x Time Since Rebate (16 months)	**2.200**	**0.275**	**7.994**
Month D	yes	yes	yes
Merchant Number D	yes	yes	yes
Merchant Number D x Month D	yes	yes	yes
Customer Number D	yes	yes	yes

Table 3.12: Results

Falsification Test: Cumulative usage at Non rebate merchants

Our second robustness check is the falsification test where we document whether the same set of customers who showed change in behavior in the rebate merchants also had a change in behavior in non participating rebate merchants. To do so, we take advantage of the merchants that were not part of the rebate program and look at the transaction behavior before and after the “artificial” rebate events.

This falsification test will allow us to discern if it was the rebate that changed the behavior of consumers’ cumulative card usage by looking for whether the same change in behavior occurred in non rebate participating merchants. While it is conceivable that the program could have had a spillover effect on the propensity to use the same card more frequently, if we find that consumers are different in their card usage at non rebate participating merchants, we are able to make a more credible case that it is the rebate that has shifted consumer behavior in the rebate merchants, not some systematic shift in unobservable consumer taste.

We first look for evidence of change in consecutive usage by doing a before and after analysis that we employed in the data section for the within network of rebate merchants. Like we have constructed the consecutive card usage that resets when the merchant rebate kicks in, we also created the consecutive usage in the same manner.

Month	Change in Cumulative Usage from Before "Rebate"
1	+8.59%
2	+8.51%
3	+4.50%
4	+0.24%
5	-1.19%
6	-5.58%

Table 3.13: Consecutive Usage of a card before and after "rebate" kicks in falsification

Given this is a falsification test, there is no actual time in which the rebate was introduced. Therefore to run this, we took the first 6 months since the introduction of the rebate program as event studies to see any change in the before and after cumulative card usage. Also, we balanced the sample so that the transaction length before and after the treatment are identical. In comparison to what we have found in the rebate merchants, the increase in consecutive usage in the non rebate merchants are significantly lower as shown above.

We note that before making any conclusion based on the above finding, we need to be aware of potential substitution effects. This is because a consumer may decide to substitute away from all coffee shops that is out of network after rebate begins since one of the merchants participating in the program is a coffee shop. And if this is occuring, we may overestimate the impact of the changes in before and after consecutive usage in network versus out of network. To be sure that this is not confounding our statistics above, we look at the before and after merchant types that the consumers shopped at.

Month Since Rebate	Change in Unique Merchants shopped	Intersection w/ Rebate Merchants
1	+0.81%	100%
2	+2.41%	100%
3	+3.17%	100%
4	+2.40%	100%
5	+2.14%	100%
6	+1.35%	100%

Table 3.14: Change from before "rebate"

As shown, we find that the merchant types shows an increase. This is promising because if there was a substitution effect going on, we would perhaps see a decrease in unique merchants shopped after the rebate is introduced.

We also look at the intersection of merchant type between in network and out of network for before and after rebate. Some examples of the merchants types are "Grocery Stores", "Fashion", "Shoe and Bags" as mentioned in section 3.1.1.

As shown above, we do not see any changes in the intersection of merchant type in the falsification. All merchant types in the rebate network were present in both regimes.

While this is reassuring, we are interested in whether the frequency of the transactions changed in the type of stores that eventually provided rebate to customers. To understand this change in overall frequency, we look at before and after frequency of all the merchant types of the rebate network in our falsification study.

Month	Change from before rebate
1	+4.64%
2	+4.39%
3	+4.05%
4	+4.41%
5	+4.49%
6	+4.68%

Table 3.15: Total transactions within merchant type of rebate program

We find that the number of transactions in the type of merchants that is part of the rebate program show a general increase after the rebate "treatment". This is encouraging as if there is a substitution effect going on, we would expect a decrease in the total usage of the type of merchants found in the network of rebate program.

Lastly, we run the following regression that we ran in section 3.4.2, to systematically discern the impact of the "rebate" on cumulative usage. We rewrite the regression below,

$$\begin{aligned} CumulativeUsage_{icjt} &= \beta_0 + \beta_1 RebateRollOut_{jt} + \beta_2 TransactionSize_{icjt} + \beta_3 CardLevelRanking_{icjt} \\ &+ \sum_{t=4}^{15} \beta_t Month_t + \sum_{j=16}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i \\ &+ \sum_{k=N+1}^{K} \beta_k (MerchNumber \times Month)_k + \epsilon_{ijt} \end{aligned}$$

There are approximately 8 times more merchants in the falsification test data thus when we interact the two terms (MerchNumber and Month) we have approximately 48,000 additional parameters to estimate. Estimating this was not feasible so we ran the above model up to the customer fixed effect.

To make a fair comparison with what we have ran in section 3.4.2, we take the result for same specification which had β_1 estimate of 5.219 (t value 19.796) included in the appendix.

	1			2			3		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	1.856	1.099	1.686	1.862	1.069	1.741	1.802	1.038	1.735
AfterRebate	**3.405**	**1.309e-01**	**26.013**	**3.26**	**1.192e-01**	**27.345**	**2.92**	**1.098e-01**	**26.597**
Transaction Amount	-1.221e-04	6.931e-05	-1.761	-1.185e-04	6.744e-05	-1.758	-1.175e-04	6.551e-05	-1.794
Rank	-8.602e-01	9.502e-02	-9.053	-8.710e-01	9.246e-02	-9.421	-9.089e-01	8.892e-02	-10.119
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes
MerchD	yes	yes	yes	yes	yes	yes	yes	yes	yes
CustomerD	yes	yes	yes	yes	yes	yes	yes	yes	yes

	4			5			6		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	1.5	9.954e-01	1.507	6.829e-01	9.687e-01	0.705	-2.283e-01	9.383e-01	-0.243
AfterRebate	**2.558**	**1.008e-01**	**25.381**	**2.505**	**9.474e-02**	**26.44**	**2.369**	**9.192e-02**	**25.772**
Transaction Amount	-1.151e-04	6.282e-05	-1.832	-1.089e-04	6.114e-05	-1.780	-9.778e-05	5.927e-05	-1.650
Rank	-8.655e-01	8.613e-02	-10.049	-8.528e-01	8.383e-02	-10.172	-8.521e-01	8.127e-02	-10.485
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes
MerchD	yes	yes	yes	yes	yes	yes	yes	yes	yes
CustomerD	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 3.16: Consecutive Usage of a card before and after “rebate” kicks in in non rebate merchants

As shown above, the impact of “rebate” is less than 5.219, the effect that we found in the rebate data. In addition, an increase of 5.219 consecutive transactions in rebate merchant is signicantly larger than 2.37-3.41 if we take into account the fact that the consecutive transactions in the rebate merchants is 0.37 of the merchants outside of the rebate network.

3.4.5 Implication of Amassing Rebates on Card Level Benefits

Having found evidence that consumers are indeed using the same card more frequently, we want to understand the implication of this behavior on optimal card choice. Below is the change in before and after mean rank of card transaction in both rebate stores and non rebate stores.[20]

[20]We determine the rank based on the value that each cards bring to a given transaction. Since each cards are given some benefits, there is a $ value attached to each card for each transaction. For example, the greatest dollar value comes when a gas card is used in gas station. Therefore, since the rebate program offers same amount of dollar rebate, consumers should in theory optimize their card usage based on what card gives them greatest benefit and ignore the rebate program.

	Percentage change in card rank from before rebate
Mean Rank of Card at Rebate Merchants	+10.67%
Mean Rank of Card at Non Rebate Merchants	+2.70%

Table 3.17: Change in rank of the card chosen after rebate

We find that perhaps consumers may be compromising the card level benefit in rebate merchants after the rebate is introduced due to their propensity to use one card more frequently to accrue rebate. To control for confounds, we run the following regression,

$$
\begin{aligned}
CardlevelRanking_{ijt} &= \beta_0 + \beta_1 RebateRollOut_{jt} + \beta_2 TransactionSize_{ijt} + \sum_{t=3}^{14} \beta_t Month_t \\
&\quad + \sum_{j=15}^{M} \beta_j MerchNumber_j + \sum_{i=M+1}^{N} \beta_i CustomerNumber_i + \epsilon_{it}
\end{aligned}
$$

	1			2		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	1.462	0.0182	80.447	1.462	0.025	58.557
AfterRebateRoll	**0.155**	**0.019**	**8.235**	**0.161**	**0.020**	**8.177**
Month D	No	No	No	yes	yes	yes
Merch Number D	No	No	No	No	No	No
Custo Number D	No	No	No	No	No	No

	3			4		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	1.230	0.235	5.239	1.486	0.136	10.915
AfterRebateRoll	**0.066**	**0.013**	**5.114**	0.0320	0.023	1.361
Month D	yes	yes	yes	yes	yes	yes
Merch Number D	No	No	No	yes	yes	yes
Custo Number D	yes	yes	yes	No	No	No

Table 3.18: Rank of the card After Rebate

As shown above, for the first two specifications, we find that the impact of rebate program is positive and significant on ranking, suggesting a compromise effect of card level benefits after rebate is introduced. Even after controlling for consumer specific differences, we find that there is a positive impact ie) significantly more of the worse cards are used after the rebate begins.

Once we include the merchant fixed effect however the significance goes away. Looking at those merchants that explains away the variation of card level rankings, we find that merchants P, CP are the leading merchants that have the greatest positive impact on consumers' propensity to "compromise" optimal card usage.[21]

There are a couple of explanations for why we no longer find a significant rebate impact after we include the merchant fixed effect. We suspect that this is because these merchants have greatest presence in Singapore where the variation in inefficient card usage are explained away when we include the fixed effect. Out of about 500 merchants that become part of the network, the largest share of merchants in the network during the period we study is P (25%) followed by R(15%) and CP (8%).

If inefficient card usage is occuring in these stores, the question is what is the source of the inefficiency? For P stores, the typical transaction size is small. Therefore, one can imagine that the inefficiency (average increase in ranking of 0.995) can be explained by consumers wanting to redeem the rebate using that card that will give them the largest percentage off from a given transaction. So while the card itself is not the most beneficial one to use in a given transaction, if a consumer will get majority of the transaction size back from rebate redemption, the consumer would be less hesitant to use the worse card. On the other hand, inefficiency may come from the fact that consumers may be saving up the rebate on a single card. For the case of CP, this may be occuring because the size of the transactions are typically large. The average increase in ranking is 0.539.

To find what is driving the increase in ranking at the two merchants with greatest positive impact on the compromise effect, we look at the redemption behavior in both shops. If majority of consumers are redeeming rebate in most transactions, the decrease in ranking is not driven by the deisre to save up. However, if this is not the case, we have evident of consumers compromising their card precisely because of their desire to save up. Looking at the redemption pattern, we find average redemption is less than 50% for each CP and P respectively, suggesting that the increase in ranking is due to consumers saving up rebate on a single card. Overall, we find that the introduction of the rebate program has made the card level choice less optimal due to consumers' propensity to save on a single card. This effect is most pronounced in two stores in the rebate network.

[21] We look at merchant fixed effect that was significant at the 0.001 level. There were a total of 8 merchants that had a significance level of 0.001 or less. There were a total of 42 merchants that had significant fixed effects less than 0.05. (37/42 being positive)

3.5 Conclusion

Using field data, our primary goal in this paper was to answer the question posed by Richard Thaler et al regarding how consumers spontaneously frame options they are faced with. We took advantage of the unique features of the rebate program to first determine that consumers' choices depart from the normative prescription of economic theory. We then used the data to empirically identify how consumers spontaneously frame reward options they are faced with.

We find evidence that consumers frame the rebate in terms of "losses". We examine and demonstrate that consumers not only wait for the optimal time to redeem, where redemption coincides with larger percentage off than previous opportunities, but also put significant effort to amass rebates on a single card. Since consumers are unable to consolidate accrued rebates across cards, we investigate the extent to which consumers use the same card and find that they forgo card-level benefits made available to them. Our results suggest that to increase redemption activity, the card company should partner up with merchants that are both small and large in transaction sizes.

Our empirical analysis hinged on the variation of time in which the rebates were rolled out and the variation of consumer behavior in both the participating and non participating rebate merchants. The richness of the data enables us to identify consumers' overall change in consumption behavior after the rebate program is introduced.

We note that the analysis looked at the overall consumption behavior controlling for any variation from customers and merchants. Our reasons for this were twofold. First, we wanted to have an understanding of the overall impact the program had on general consumers before looking at difference in behavior across each individuals. Second, while the data was made available for 16 months since the introduction of the rebate, given the gradual roll out of merchants, the number of transactions per customer and their movement across merchants were more limited than we had originally thought. For example, from what we have found, one can imagine that consumers save up in stores with large transaction size and redeem in store that require small transaction, such as the coffee shops. However, this pattern was not observed frequently in our data. We believe that this is due to the relatively limited stores that consumers were able to redeem, at least in the first few months of the program. Moving forward, our hope is that we supplement the data that spans additional years. By doing so, we can leverage this to model consumer utility that takes into account the identity of the merchants.

The findings in this paper alone have implications for designing a more active rebate program. Even so, there is much more that can be done moving forward. Despite understanding the demand side of the program is paramount, the current state of the payment structure makes it clear that taking the supply side of the program into account is equally important. The payment structure depends on the merchant such that the rebate is either paid in full by the bank, by the merchant or split between the two. This begs the question of what the optimal strategy is for the bank. Since cross-merchant redemption is allowed in the program, it is not so clear which merchants to include or exclude. Our hope is to continue the analysis that takes the supply side into account to give managerially relevant recommendations to designing an optimal assortment of merchants in the rebate program.

Lastly, it would be interesting if some of the existing program features were tested for its efficacy. One of the reasons given to us on why the "instant" rebate is made available only in the next transaction is because there is a "lock in" effect for customers to return. However, as found in the analysis above, one can argue that consumers may be more engaged if rebates were provided at the same transaction since the propensity for redemption increases with the discount size. This is an empirical question that can be tested in the field. This is left for future work.

Bibliography

[1] Rao, A. R, R. Ruckert. “Brand Alliance as signals of product quality”, Sloan Management Review 36 (Fall) 87-97

[2] Segrave, Kerry. “Endorsements in Advertising, A social history” McFarland & Company, Inc., Publishers, 2005

[3] Cresswell, Julie. “Nothing Sells Like Celebrity” New York Times, Published: June 22, 2008

[4] Busler, Michael “Product Differentiation, Celebrity Endorsements and the Consumer’s Perception of Quality” 2002

[5] Agarwal, J. Kamakura, WA “The Economic Worth of Celebrity Endorsers: An event student analysis” Journal of Marketing Vol 59. July 1995

[6] Sirak, Ron. The Golf Digest 50, The rich get richer: The money on tour gets another boost (and then there’s the tidy retirement fund). No wonder Tiger’s approaching $1 billion. February 2008

[7] National Golf Foundation, “Research FAQ’s”, “http://www.ngf.org/cgi/faqa.asp#1”. Accessed July 31 2010

[8] Skidmore D, National Diversity Solutions, Economic Inclusion in Golf Industry (2008) http://www.nationaldiversitysolutions.com/pdf/National-Diversity-Solutions-Case-Study-Economic-Inclusion-in-the-Golf-Industry.pdf

[9] Answers.com, “How is a golf ball made?”, http://www.answers.com/topic/golf-ball Accessed July 31, 2010

[10] Dukcevich, D, “Nike Golf: off the ball?” Forbes http://www.forbes.com/2002/03/05/0305nike.html. March 05 2002.

[11] Stachura, Mike. The Hot list, Golf Digest, June 2010.

[12] USGA rule, “Guide to rules on clubs and balls”, http://www.usga.org/Rule-Books/Rules-on-Clubs-and-Balls/Equipment-Rules/ Accessed May 21 2012

[13] Official World Golf Ranking, http://www.officialworldgolfranking.com/home/default.sps Accessed May 21, 2012

[14] Bagwell, Kyle "The Economic Analysis of Advertising", Armstrong M, Porter RH, eds, Handbook of Industrial Organization, Elsevier, Vol. 3 Chapter 28 2007

[15] Newman, G., Diesendruck, G. and Bloom, P. "Celebrity Contagion and the Value of Objects," Journal of Consumer Research, 2011

[16] Stigler GJ, Becker GS, "De gustibus non est disputandum", American Economic Review, 76-90, 1977

[17] Becker, GS, Murphy KM, "A Simple Theory of Advertising as a Good or Bad," Quarterly Journal of Economics, 108(4), 1993

[18] Ackerberg, AD, "Empirically distinguishing informative and prestige effects of advertising", RAND Journal of Economics Vol 32, No. 2, Summer 2001 pp 316-333

[19] Berry S, Levinsohn J, Ariel P, "Automobile Prices in market equilibrium". Econometrica Vol 63 No.4 (July 1995) 841-890

[20] Skrainka, BS., Judd KL. High Performance Quadrature Rules: How Numerical Integration Affects a Popular Model of Product Differentiation. Working Paper, 2012.

[21] Berry, S., Linton OB, Pakes A, "Limit Theorems for Estimating the Parameters of Differentiated Product Demand Systems," The Review of Economic Studies, 71(3) 2004

[22] McLaughlin, Mark. "Nike, Titleist wage ball battle" April 4 2001. CNN Money http://money.cnn.com/2001/04/04/companies/ballwars/index.htm

[23] Thaler R, Eric Johnson, "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice", Management Science, Vol 36, No. 6, June 1990.

[24] Kahneman D, Amos Tversky "Prospect Thoery: An Analysis of Decision under Risk" Econometrica Vol 47 No 2 (Mar., 1979) pp 263-292

[25] Markowitz, H. "The Utility of Wealth", Journal of Political Economy., 60,2 (1952), 151-158

[26] Prelec D, George Lowenstein "Decision Making Over Time and Under Uncertainty: A Common Approach" Management Science Vol 37 No 7 July 1991

Appendix

Chapter 2

The Golf Equipments

Golf Bags

Golf bags are designed to transport the golf clubs which are used to play the sport of golf. There are two main type of bags, a stand bag and a cart bag. Stand bags are usually smaller and made with lighter material with retractable v-shaped tripod-like stand while cart bags are larger in size made with heavier material. Stand bags are primarily used for golfers who carry their own golf bags when playing the sport of golf. Cart bags are used either by professionals who have “caddies”[22] or by golfers who primarily use golf carts to play golf.

Golf Clubs

In a golf bag, there are typically 14 golf clubs[23]. Golf clubs are the equipment used in the sport of golf to hit golf balls. Each club is made up of a shaft and a club head. Within golf clubs, there are 3 main different types of clubs; Woods, irons and putters. Woods are traditionally the longest type of clubs with the longer shafts and larger club head, used mainly for long distance shots. Traditionally, there are 3 woods in a bag, a 1 wood (Driver), 3 wood (fairway wood), 5 wood (fairway wood), with 1 wood being the longest and the lowest lofted club head. It is called “Woods” because the club head was traditionally made of hardwood. Today, no longer are the woods made up of wood materials but rather metal materials like titanium and steel. 1 wood is called the “driver” because

[22] A caddie is a person who carries the golf bag for the player in a tournament. Other than carry the bag, good caddies usually provide advice on the course with strategies to which the player should play. Also, good caddies are known to give moral support for the player.

[23] United States Golf Association (USGA), the national governing body of golf for the US and Mexico states under section III rule 4-4 that the player must not start a round with more than 14 clubs. Fewer than 14 clubs are permitted.

they are the largest and the longest club in a golf bag that are primarily used for the first tee shot in each golf holes. First shots are called the “tee shot” because players are allowed to use the wooden “tee” to elevate the golf ball from the ground before hitting the ball with the golf club. 3 woods and 5 woods are also called the “fairway woods” because they are designed for shots that are long in distance from the hole from the fairway. Irons are the most versatile clubs that consist of different length of shafts with different loft of club head face. In iron clubs, there are two types of club head face. The more traditional of the two are the “blades” or the “muscle back blades” which are typically recommended for lower handicap (better player) players. It is estimated that blade irons account for only about 2% of sales in the market (2006 GolfDigest). The more common type of irons are the “cavity back”, the name referring to a “cavity” created from a small amount of metal in the back of the club face removed. These clubs are more forgiving and are recommended for all type of golfers. The iron clubs are traditionally numbered from 3- 9 with 3 being the the longest with the smallest loft. The purpose of the lower numbered iron clubs are for shots that are longer in distance with a ball flight that will result in a low trajectory. On the other hand, higher numbered irons are shorter in length providing shorter distance with a higher launch angle resulting from a lofted club face. Part of the iron sets that are not numbered are the wedges. Wedges are irons with even higher loft than a 9 iron, used primarily to make short shots near the green surface.There are 4 types of wedges;Pitching wedge, Gap wedge, Sand Wedge and Lob Wedge. Pitching wedge is the least lofted wedge with the loft between 44 to 50 degrees. Gap wedges, generally has a loft between 46 to 54 degree, while Sand Wedge is between 54 to 58. Sand wedge, as the name implies is used for golfer to hit the ball out of the sand traps hazard that are typically located around the green surface. Lastly, the Lob Wedge range from 60 to 65 degrees which helps the golfer hit the ball high up in the air. The loft of the wedges are inversely related to the distance traveled. Once the golf ball lands on the green or the “putting” surface, which is the portion of the golf course that consists of the shortest and closely cropped grass, players use the putter to roll the golf ball into the cup. Putters are the type of clubs that are most varied in design, both in length and shape. A typical golfer would carry 3 woods, iron set (7 clubs), 2-3 wedges, and a putter.

Reduced Form Robustness Check

In this section we report robustness checks of our reduced form models. One may think that our parametric assumption on the endorsement variable may be too restrictive. Consequently, we also employ a non parametric form of the exogenous ranking variable that estimates the effect of each rank while preserving the rank order. The advantage of this is obvious in that we do not have to make any assumption regarding the endorsement variable. However, the disadvantage of estimating the effect of each rank is that we lose statistical power as each rank of a player is now considered a variable of its own. For example, during 159 months that we study, David Duval had 50 unique world ranking. Therefore, on average a little more than 3 data points would be used to estimate each ranking effects. Similarly, for Tiger Woods, while he has been more consistent in performance during this period, we also have instances in which a specific ranking is represented only once. For example, we have that Tiger Woods was ranked 5, 14, 15 and 22 only once during his duration of 159 months. To alleviate this loss in power, we group each player's ranking variables into one of three bins–rank of 1, 2<rank<5 and rank greater or equal than 5. By doing so, we are able to estimate separate ranking effect in a more reasonable manner as it alleviates the loss of statistical power. In fact, when we estimate the non parametric form without this grouping, our standard errors for each ranking effect are an order of magnitude larger, leading to many ranking effects to be insignificant. We also test the robustness of the specific shape of our parametric form by varying the degree of decay of the ranking variable above. These addtional models illustrate that our parametric form results in the paper are robust to other specifications

In the table below we report the results of the non parametic estimator, excluding the month and year fixed effect to preserve space. However, the year effects were all significant except for year 1998 and 1999. As shown from our R^2 statistics, the model fits well with 98% of variance being explained by the regressors. As expected, we see that the Titleist fixed effect is large and positive as the Titleist brand has consistently outsold the other two brands in our data. For the ranking variables, we find significant estimate for 3 out of 5 endorsers. In the case of Tiger Woods and David Duval, we find that when ranked 1, the effect is largest while showing decreasing effects through rankings. In fact, we have a general downward trend of the endorsement effect on log(sales) even for endorser who show no statistical significance. For example, for both Ernie Els and Phil Mickelson, we can see that the effect decreases as the ranking variable goes up.

Also, below is the graphical representation of the non parametric estimate of the ranking variable of two endorsers Tiger Woods and David Duval. As mentioned, we have a general downward shape of the endorsement effect. In the case of Tiger Woods, while his effect shows a slight increase from rank [2,4] to 4<rank, the general downward trend is encompassed in the 95% confidence interval. For David Duval, we see a clear downward effect of each endorsement variable on log(sales). Lastly, we have a differing width of the confidence interval for two players as each ranking variables are not equally represented in the data. Mainly, for the case of Tiger Woods, rank of 1 has a smaller interval while for Duval this is reversed as the ranking during the majority of Duval's playing career has been outside 4.

	Estimate	Std. Error	t value	Sig
(Intercept)	2.697	0.105	25.605	***
Unplanned Exposure	0.003	0.010	0.365	
4<Rank of Tiger Woods	0.628	0.129	4.854	***
1<Rank of Tiger Woods<5	0.577	0.078	7.356	***
Rank of Tiger Woods =1	0.712	0.052	13.613	***
4<Rank of David Duval	0.308	0.051	6.016	***
1<Rank of David Duval<5	0.406	0.051	7.888	***
1/Rank of David Duval=1	0.495	0.126	3.932	***
4<Rank of Ernie Els	-0.046	0.056	-0.817	
1<Rank of Ernie Els<5	0.021	0.056	0.372	
1/Rank of Ernie Els=1	0.199	0.148	1.35	
4<Rank of Phil Mickelson	-0.015	0.054	-0.283	
2<Rank of Phil Mickelson<5	0.015	0.060	0.248	
1/Rank of Phil Mickelson=2	0.168	0.060	2.793	***
4<Rank of Vijay Singh	0.123	0.059	2.079	***
1<Rank of Vijay Singh<5	0.096	0.062	1.541	
1/Rank of Vijay Singh=1	0.042	0.087	0.486	
Brand Fixed Titleist	1.529	0.055	27.947	***
Brand Fixed Nike	-0.729	0.062	-11.677	***
R^2	0.9757			
Adjusted R^2	0.9729			

Note: Sales is in 1000's of dozen Balls

Note: Signif. codes: 0 < *** < 0.05< ** <0.1

Table 3.19: Regression of Log(Sales) on Non Parametric Endorsement Variable

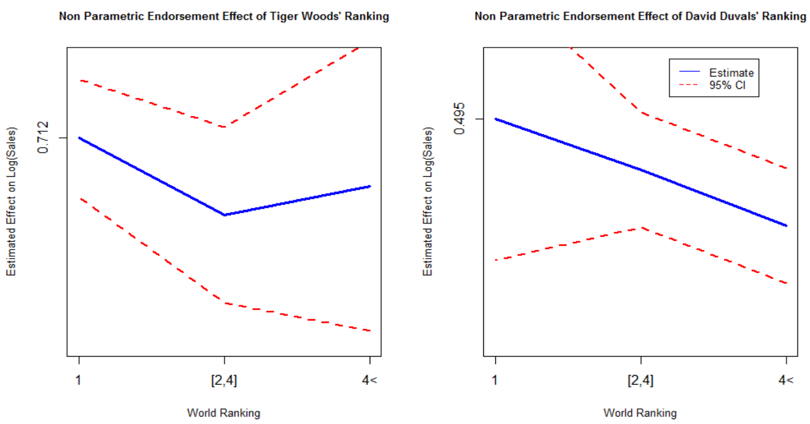

Figure 3.5: Non Parametric Estimate of the Ranking Effect on Log(Sales)

Market Size/Outside Goods Variable

In this section, we describe our method of market size determination of 40 million per year. Our determination consists of the known size of the two segments of golfing population (avid, non avid) and the unknown but assumed level of consumption within each segments. Once the market size is determined, we use the quantity sold to ensure that we have large enough share of outside option of no purchase.[**?**]

What is known to us is that in the past 10 years, the number of golfers remained steady at 26 to 30 million in the United States. We take 28 million as the total number of golfing population in the US. Out of this, the avid golfers (players who play 25 rounds or more per year) make up 23% of all golfers.[**?**] With this information, we have the remaining 77% to be the non avid golfers who we assume to play less than 5 rounds of golf per year. These known figures gives us approximately 6.4 million avid golfers and 21.6 million non avid golfers.

Having defined the size of two golfing segments, to estimate the market size of golf ball consumption, we need to consider the amount of golf ball consumed during each round of golf for each segments. This is important to take into account as per round golf ball consumption across two segments vary dramatically. However, per round ball consumption level (ie: amount of ball "lost" during a round of golf) is not known to us. We approximate this with the institutional knowledge that tells us that the per round golf ball consumption is inversely correlated to the total number of golf round consumption. In other words, avid golfers are in general better skilled golfers and as a result of this lose fewer balls per round (although their overall consumption can make up through the frequency of play per year). We assume that avid golfers typically need 1 golf balls per round which means on average they consume 25 golf balls per year (25 x 1). For the non avid golfers, we assume that they consume approximately 4 golf balls per 18 hole round meaning an average consumption of 20 golf balls per year (4 x 5). On any purchase occasion, golf balls are sold in dozens which is the sales unit of our data. Therefore, we have that both avid and non avid players on average purchase 1~2 dozen of golf balls per year. With this, we multiply the total segment size by the consumption level and sum up the values which approximates to 40 million. Using this figure we are able to back out the share of outside good of no purchase for each market (month) where we have that the outside share ranges from 0.196 to 0.820. As mentioned, this is expected as golf ball sales are highly seasonal and we have not assumed varying market size over time (month). The lower bound represents the summer months when golf ball sales are high while the upper bound represents winter months when golf ball sales are stagnant as a result of weather condition that prevents golfers from playing golf. We include the plot of this in the appendix.

We acknowledge that we have made a series of assumptions to come up with the market size of 40 million. This assumption is important as it determines the size of outside good which affects our demand estimation. Even though we have made every attempt to approximate the unknown market size as accurately as possible, we realize its limitation as one may view this exercise as ad hoc at best. To alleviate this, we check the sensitivity of our results to different market size definition. To this end, we estimate both the OLS and 2SLS of the demand model by starting from the market size of 35 million and incrementally increasing at 2.5 million until 50 million. Our estimate suggests that the parameters of interest are not sensitive to the market size.

Outside option of No purchase

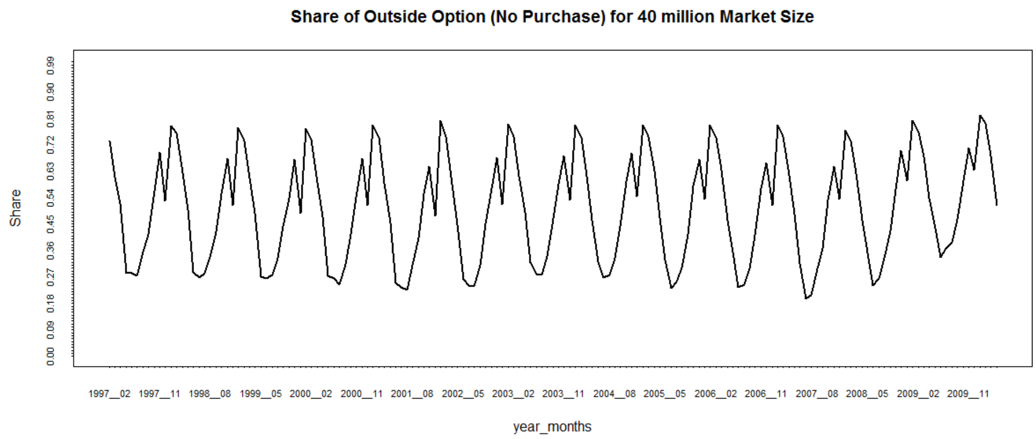

Figure 3.6: Outside Share with market size assumption of 40 million

Above we plot the time series plot of the outside option of no purchase under our assumed market size of 40 million. As it can be readily seen, given that we assume constant market size for each market (month), there is high variation across time as golf ball sales is highly seasonal. We take into account this in our indirect utility function by including time fixed effects (month, year interaction fixed effect variable).

Estimation Results (OLS and 2SLS)

OLS				2SLS			
Linear Parameters	**Estimate**	**SE**	**Estimate/SE**	**Linear Parameters**	**Estimate**	**SE**	**Estimate/SE**
Price	-0.048	0.002	-31.049	Price	-0.089	0.002	-43.239
Winning of Tournaments (unplanned exposure)	0.020	0.014	1.490	Winning of Tournaments (unplanned exposure)	0.021	0.014	1.426
Woods Scandal on Nike products (12.2009-01.2010)	0.004	0.111	0.033	Woods Scandal on Nike products (12.2009-01.2010)	-0.044	0.089	-0.498
Woods Scandal on Nike products (02.2010-04.2010)	-0.120	0.115	-1.044	Woods Scandal on Nike products (02.2010-04.2010)	-0.180	0.094	-1.921
Woods Nike Endorsement	0.280	0.082	3.400	Woods Nike Endorsement	0.302	0.079	3.826
Duval Nike Endorsement	-0.269	0.235	-1.146	Duval Nike Endorsement	-0.387	0.244	-1.586
Mickelson Callaway Endorsement	1.041	0.216	4.820	Mickelson Callaway Endorsement	1.299	0.206	6.302
Els Callaway Endorsement	0.965	0.315	3.065	Els Callaway Endorsement	m.357	0.311	4.357
Woods Titleist Endorsement	0.243	0.067	3.630	Woods Titleist Endorsement	0.291	0.074	3.922
Mickelson Titleist Endorsement	-0.325	0.150	-2.171	Mickelson Titleist Endorsement	-0.340	0.192	-1.769
Duval Titleist Endorsement	0.420	0.101	4.142	Duval Titleist Endorsement	0.488	0.106	4.628
Singh Titleist Endorsement	-0.080	0.095	-0.847	Singh Titleist Endorsement	-0.121	0.093	-1.306
Els Titleist Endorse	0.607	0.113	5.353	Els Titleist Endorse	0.668	0.136	4.913

Table 3.20: Estimate of the Logit Model-OLS (Benchmark) and 2SLS

	OLS						
Market Size (million)	35	37.5	40	42.5	45	47.5	50
Price	-0.048 (0.002)	-0.048 (0.002)	-0.048 (0.002)	-0.048 (0.002)	-0.047 (0.001)	-0.046 (0.001)	-0.045 (0.001)
Winning of Tournaments (unplanned exposure)	0.023 (0.015)	0.023 (0.014)	0.02 (0.014)	0.02 (0.013)	0.021 (0.013)	0.022 (0.013)	0.022 (0.013)
Woods Scandal on Nike products (12.2009-01.2010)	-0.023 (0.123)	-0.019 (0.115)	0.004 (0.111)	0.022 (0.108)	-0.02 (0.106)	0.03 (0.104)	0.007 (0.102)
Woods Scandal on Nike products (02.2010-04.2010)	-0.158 (0.127)	-0.148 (0.119)	-0.12 (0.115)	-0.133 (0.112)	-0.132 (0.11)	-0.069 (0.108)	-0.061 (0.106)
Woods Nike Endorsement	0.254 (0.091)	0.279 (0.086)	0.28 (0.082)	0.303 (0.081)	0.296 (0.079)	0.309 (0.077)	0.277 (0.076)
Duval Nike Endorsement	-0.198 (0.26)	-0.258 (0.244)	-0.269 (0.235)	-0.248 (0.23)	-0.291 (0.225)	-0.329 (0.221)	-0.346 (0.217)
Mickelson Callaway Endorsement	1.037 (0.239)	1.1 (0.224)	1.041 (0.216)	1.066 (0.211)	1.082 (0.206)	1.056 (0.203)	1.097 (0.199)
Els Callaway Endorsement	1.015 (0.349)	1.006 (0.327)	0.965 (0.315)	0.885 (0.308)	0.869 (0.301)	0.76 (0.296)	0.806 (0.291)
Woods Titleist Endorsement	0.221 (0.074)	0.234 (0.069)	0.243 (0.067)	0.234 (0.065)	0.225 (0.064)	0.216 (0.063)	0.218 (0.062)
Mickelson Titleist Endorsement	-0.338 (0.166)	-0.357 (0.156)	-0.325 (0.15)	-0.348 (0.146)	-0.389 (0.143)	-0.391 (0.141)	-0.389 (0.138)
Duval Titleist Endorsement	0.422 (0.112)	0.421 (0.105)	0.42 (0.101)	0.409 (0.099)	0.405 (0.097)	0.419 (0.095)	0.412 (0.093)
Singh Titleist Endorsement	-0.066 (0.105)	-0.075 (0.098)	-0.08 (0.095)	-0.086 (0.092)	-0.092 (0.09)	-0.093 (0.089)	-0.099 (0.087)
Els Titleist Endorse	0.583 (0.126)	0.597 (0.118)	0.607 (0.113)	0.605 (0.111)	0.609 (0.108)	0.625 (0.106)	0.597 (0.105)
	2SLS						
Market Size (million)	35	37.5	40	42.5	45	47.5	50
Price	-0.091 (0.002)	-0.091 (0.002)	-0.089 (0.002)	-0.087 (0.002)	-0.085 (0.002)	-0.083 (0.002)	-0.082 (0.002)
Winning of Tournaments (unplanned exposure)	0.023 (0.016)	0.023 (0.015)	0.021 (0.014)	0.02 (0.014)	0.021 (0.014)	0.023 (0.013)	0.022 (0.013)
Woods Scandal on Nike products (12.2009-01.2010)	-0.073 (0.095)	-0.069 (0.091)	-0.044 (0.089)	-0.025 (0.088)	-0.065 (0.086)	-0.014 (0.084)	-0.036 (0.083)
Woods Scandal on Nike products (02.2010-04.2010)	-0.221 (0.098)	-0.21 (0.098)	-0.18 (0.094)	-0.192 (0.092)	-0.189 (0.088)	-0.124 (0.087)	-0.114 (0.084)
Woods Nike Endorsement	0.277 (0.092)	0.302 (0.083)	0.302 (0.079)	0.325 (0.077)	0.316 (0.074)	0.329 (0.072)	0.297 (0.07)
Duval Nike Endorsement	-0.321 (0.269)	-0.38 (0.256)	-0.387 (0.244)	-0.363 (0.239)	-0.402 (0.232)	-0.436 (0.226)	-0.451 (0.219)
Mickelson Callaway Endorsement	1.307 (0.225)	1.367 (0.215)	1.299 (0.206)	1.317 (0.204)	1.324 (0.197)	1.291 (0.194)	1.326 (0.192)
Els Callaway Endorsement	1.425 (0.337)	1.412 (0.321)	1.357 (0.311)	1.267 (0.305)	1.239 (0.298)	1.117 (0.291)	1.155 (0.287)
Woods Titleist Endorsement	0.272 (0.084)	0.284 (0.077)	0.291 (0.074)	0.282 (0.073)	0.271 (0.071)	0.261 (0.07)	0.262 (0.069)
Mickelson Titleist Endorsement	-0.354 (0.209)	-0.373 (0.198)	-0.34 (0.192)	-0.362 (0.188)	-0.403 (0.185)	-0.404 (0.182)	-0.402 (0.179)
Duval Titleist Endorsement	0.494 (0.125)	0.492 (0.11)	0.488 (0.106)	0.475 (0.102)	0.47 (0.1)	0.481 (0.099)	0.473 (0.097)
Singh Titleist Endorsement	-0.109 (0.101)	-0.118 (0.096)	-0.121 (0.093)	-0.126 (0.091)	-0.131 (0.09)	-0.131 (0.088)	-0.136 (0.087)
Els Titleist Endorse	0.647 (0.154)	0.66 (0.141)	0.668 (0.136)	0.664 (0.132)	0.666 (0.129)	0.681 (0.126)	0.651 (0.124)

Note: Estimate (Standard Error)

Table 3.21: Robustness Check on Market Size

Chapter 3

	1 (Linear Model)			2 (Linear Model)			1(logit)			2(logit)		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	0.723	0.091	7.965	0.540	0.196	2.753	-15.160	2093.000	-0.007	-15.320	5690.000	-0.003
Accumulated Rebate on card	**-0.010**	**0.001**	**-14.922**	**-0.001**	**0.001**	**-1.157**	**-0.054**	**0.004**	**-13.666**	-0.008	0.005	-1.839
Potential % off	**0.258**	**0.030**	**8.727**	**0.553**	**0.030**	**18.730**	**1.388**	**0.150**	**9.229**	3.821	0.199	19.231
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Merchant Number D	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Customer Number D	no	no	no	yes	yes	yes	no	no	no	yes	yes	yes

Table 3.22: Redemption

dataM4	1			2			3			4			5		
Cumulative Usage	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	3.979	0.359	11.074	0.245	1.832	0.134	-1.423	6.763	-0.210	-4.402	4.801	-0.917	-2.322	8.930	-0.260
AfterRebateRoll	**4.268**	**0.265**	**16.127**	**4.887**	**0.314**	**15.550**	**5.741**	**0.403**	**14.237**	**5.219**	**0.264**	**19.796**	**6.187**	**0.335**	**18.477**
Transaction size	-0.002	0.001	-3.579	-0.001	0.001	-1.875	-0.002	0.001	-1.968	0.000	0.001	-0.641	-0.001	0.001	-0.864
Rank of Card	-0.404	0.087	-4.659	-0.468	0.088	-5.333	-0.492	0.094	-5.245	-0.097	0.127	-0.761	-0.191	0.143	-1.336
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Merch Number D	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Custo Number D	no	no	no	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes
Month D x Merch number D	no	no	no	no	no	no	yes	yes	yes	no	no	no	yes	yes	yes

Table 3.23: Regression Results

dataM4-trunc	1			2			3			4			5		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	4.773	0.604	7.900	0.134	2.057	0.065	4.828	2.403	2.009	1.903	4.726	0.403	3.841	4.440	0.865
AfterRebateRoll	**-1.649**	**0.272**	**-6.065**	**-0.095**	**0.381**	**-0.251**	**-0.151**	**0.389**	**-0.389**	**1.589**	**0.574**	**2.770**	**1.278**	**0.593**	**2.156**
Transaction size	-0.011	0.002	-4.870	-0.003	0.003	-1.101	-0.001	0.003	-0.292	-0.002	0.002	-1.070	-0.001	0.003	-0.359
Rank of Card	0.178	0.206	0.863	0.280	0.220	1.272	0.238	0.314	0.758	0.364	0.216	1.682	0.157	0.350	0.450
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Merch Number D	no	no	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Custo Number D	no	no	no	no	no	no	yes	yes	yes	no	no	no	yes	yes	yes
Month D x Merch number D	no	no	no	no	no	no	no	no	no	yes	yes	yes	yes	yes	yes

Table 3.24: Truncated Regression Results

	1			2			3		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value	Estimate	Std Error	t-value
Intercept	9.156	0.387	23.650	3.074	4.346	0.707	4.167	17.480	0.238
Rebate Accumulated	**0.171**	**0.015**	**11.589**	**0.054**	**0.013**	**4.192**	**0.067**	**0.014**	**4.848**
Transaction size	-0.003	0.001	-3.167	0.001	0.001	0.734	0.001	0.001	0.905
Rank of Card	-0.407	0.134	-3.046	0.024	0.229	0.105	0.135	0.264	0.512
Month D	yes	yes	yes	yes	yes	yes	yes	yes	yes
Merch Number D	no	no	no	yes	yes	yes	yes	yes	yes
Custo Number D	no	no	no	yes	yes	yes	yes	yes	yes
Month D x Merch number D	no	no	no	no	no	no	yes	yes	yes

Table 3.25: Cumulative usage after the introduction of rebate program