ESSAYS ON RELATIONSHIP MARKETING

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A Dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the Kenan-Flagler Business School.

Chapel Hill
2016

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ABSTRACT

Farnoosh Khodakarami: Essays on Relationship Marketing
(Under the direction of Rajdeep Grewal and J. Andrew Petersen)

Relationship marketing (RM) is defined as “all marketing activities directed towards establishing, developing, and maintaining successful relational exchanges” (Morgan and Hunt 1994, p. 22). Firms invest in RM activities to develop and maintain relationship with customers. Relationship marketing is not new to marketing literature. However, investigations report mixed results regarding the effectiveness of relationship marketing (Palmatier et al. 2006. Palmatier 2008). There is still need for research to guide managers on how to develop and maintain relationship with customers; which customers are better target for relationship marketing initiatives; how customer’s relationship with an organization evolve over time and when relationship marketing is more effective to enhance customer behavior. Specifically, research in relationship marketing is often studied within the frame of a single firm, due to data limitation. There has yet to be much research that sheds light on how customers build and maintain relationship with multiple firms in a competitive environment. In this dissertation, I aim to answer these questions with two studies.

In the first study of this dissertation, in a non-profit context, I study the drivers of relationship over a customer (in this case a donor) relationship with an organization. I also examine how breadth of the relationship a donor builds with the non-profit affects donor’s behavior over time. In addition, I conduct a field study to examine whether marketing communications can help to increase the breadth of relationship donors build with the organization. In the second study of

this dissertation, I focus on reward program, which is a widely used relationship marketing strategy across industries. I examine a customer's usage of loyalty programs across competing firms, to see how a customer's relationship with one firm and redeeming a reward at this firm impacts that customer's future search and transaction behavior at the focal firm as well as with competing firms. I also investigate the impact of redeeming a reward on heavy users and light users to see if reward programs induce different responses from loyal customers vs. less engaged, infrequent customers.

To my parents, Minoo Hekmat and Maghsood Ali Khodakarami
The reason of what I become today.
Thank you mom and dad for all your love, support and encouragement throughout my life.

ACKNOWLEDGEMENTS

The completion of my dissertation and subsequent Ph.D. has been a long journey. It would not have been possible to do without the support and guidance that I received from several people. First, I would like to express my special appreciation and thanks to my advisors, J. Andrew Petersen and Rajdeep Grewal. I am extremely grateful to Andrew Petersen, for his invaluable guidance, scholarly input, and his continuous support throughout my Ph.D. I would like to express my sincere gratitude to Rajdeep Grewal for his support, immense knowledge, and for helping me out by accepting to serve as my co-advisor. In addition, I would like to thank the rest of my dissertation committee, Katrijn Gielens, Tarun Kushwaha, and Rajkumar Venkatesan, for their time, valuable advice and feedback through the doctoral program and dissertation work.

I also thank my best friend and soulmate, Saeed Jafaei. These past several years have not been an easy ride for me. Saeed was always there to cheer me up and help me in so many ways to deal with all the stress of Ph.D. life. I truly thank him for his love, constant support and encouragement, and for helping me gain confidence in my abilities.

Last, but certainly not least, I thank my parents, Minoo and Maghsood (Ali). I owe a lot to them, for always believing in me, and for their unconditional love and support at every stage of my personal and academic life. During the five years of my Ph.D., I have not had the chance to be with my parents for more than two weeks. It has certainly not been easy for them and me, and needed a lot of sacrifice. But they have always supported me and encouraged me to follow my dreams, and helped me in whatever way they could during this period, and throughout my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Firms rely on relationship marketing (RM) practices to develop and maintain relationship with their customers, with the goal of enhancing performance (Palmatier 2008). However, past research shows mixed results for impacts of relationship marketing on performance outcomes (e.g. Colgate and Danaher 2000 ; Palmatier et al. 2006; Srinivasan and Moorman 2005) . Specifically with regard to loyalty programs that are commonly used to enhance customers' relationship with the firm, there is still ambiguity on whether these programs can successfully increase behavior loyalty (Dowling and Uncles 1997; Leenheer et al. 2007).

A majority of studies on relationship marketing focus on antecedents of relationship between a firm and its customers. Studies have explored the role of trust, commitment, satisfaction and other motivating factors that affect the strength and duration of relationship (e.g. Ganesan 1994; Moorman, Zaltman, and Deshpande 1992; Palmatier et al. 2006; Sirdeshmukh, Singh, and Sabol 2002). However, an import issue that requires more in-depth investigation is the dynamic nature of customer-firm relationship over an extend period of time. For instance, it is important for managers to know at which stage (acquisition vs. retention) RM initiatives are more effective. Past research suggests that relationship marketing effort should be targeted at customers who are more responsive to relationship marketing (Palmatier et al. 2006). However, it is not clear that which customers are more responsive to RM initiative, or whether customers' responsiveness to RM initiatives changes over the customer life cycle. Furthermore, research in relationship marketing is often studied within the frame of a single firm, due to data limitation. However, in many industries it is common that customers transact with multiple competing firms. Thus, in order to investigate the impact of RM practices of a firm on customer behavior one needs to consider a customer's interactions across all firms, and whether these RM practices have cross-firm effects on customer behavior (Leenheer et al. 2007; Liu and Yang 2009).

In my dissertation, I aim to tackle these aspects of relationship marketing that has not been thoroughly investigated. More specifically, I aim to answer the following research questions:

What are the drivers of relationship with an organization?

How do relationships with an organization evolve over the customers' life cycle?

How do customers' relationships with multiple organizations evolve over time?

In the first essay, I answer the first two questions. Within a non-profit context, I examine whether the breadth of relationship impact performance outcomes, and whether the drivers of relationship change over time. For this study, I use the donor database of a major public university foundation. I empirically test if donors who build a broader relationship with the nonprofit are more valuable to the organization over time. I show that breadth of relationship has significant impact on donor behavior. Donors with broader relationship are more likely to give again in the next fiscal year and conditional on a gift occurring, expected value of the gift is larger. Further, these donors are more responsive to the organization's marketing communications. I also show that drivers of relationship change over time. I find in general that donor characteristics are more influential in driving the breadth of the relationship at the acquisition stage. However, as the donor-nonprofit relationship develops over time, marketing efforts from the nonprofit organization become more influential.

Knowing that donors who have broader relationship with the organization are more valuable, I conduct a field study to show that relationship marketing communications help to increase the breadth of relationship donors build with the organization.

In the second essay, I answer the third question and explore customers' relationships with multiple organizations. Customers usually are not 100% loyal to one firm and purchase across firms. Many firms offer loyalty programs, to reward their best customers and enhance the relationship with those customers. However, customers are members of and influenced by loyalty programs across many different firms. In essay 2, I investigate how a customer's reward redemption at a firm impacts that customer's future search and transaction behavior at that firm as well as with competing firms. To do this, I use a novel dataset from a mobile advertising and loyalty app provider which partners with multiple firms and allows customers to manage relationships with independent loyalty programs across those different firms. I match customers based on their probability of redeeming a reward at the focal store and find that customers who redeem a reward will visit the store more often and spend more on average, as compared to those customers who have accumulated the same amount of points, but did not redeem any reward. Interestingly, customers who redeemed a reward will also become more interested in competitive offerings, and will visit other stores more often as compared to non-redeemers. These findings suggest that redeeming a reward has positive effect on customer behavior at the focal store, but also makes them more prone to look for other offers once they utilize the points they have accumulated at that store. In other words, this study reveals that there is a spillover effect in a customer's behavior across loyalty programs across firms. This has significant implication to theory. It is impossible to demonstrate the cross-firm effect of reward redemption without observing a customer's relationships with multiple firms. Furthermore, analysis of redeemers' post-redemption behavior reveals that redeeming a reward has much more positive effect on light users as compared to heavy users. This result shows that relationship marketing practices that are targeted at light users have higher return on investment for firm.

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CHAPTER 2: DEVELOPING DONOR RELATIONSHIPS: THE ROLE OF THE BREADTH OF RELATIONSHIP[1]

Abstract

This research proposes a mechanism to develop long term donor relationships, a major challenge in the nonprofit industry. We propose a metric, Donation Variety, which captures both the depth and breadth of donations a donor has with a given nonprofit organization. Using donation data spanning twenty years from a major US public university, we find that improvements in Donation Variety increases the likelihood the donor makes a subsequent donation along with the donation amount and reduces the sensitivity of donations to negative macroeconomic shocks. In the acquisition phase, most donors give to a single initiative and that these decisions are influenced more by a donor's intrinsic motivations. In contrast, as the donor-nonprofit organization relationship develops over time, nonprofit marketing efforts have a more significant influence on a donor's decision to give to multiple initiatives. Finally, we conduct a field study that validates the econometric analysis and provides causal evidence that marketing efforts by nonprofit organizations can encourage donors to spread donations across multiple initiatives.

Keywords: Donation Variety, Field Study, Cross-buying, Donor Relationship Management

[1] This chapter previously appeared as an article in the Journal of Marketing. The original citation is as follows: Khodakarami, Farnoosh, J. Andrew Petersen, and Rajkumar Venkatesan," Developing Donor Relationships: The Role of the Breadth of Giving," *Journal of Marketing* 79, no. 4 (July 2015): 77.

Introduction

From 1999 to 2009 there has been a 59% growth in the number of public charities and a 54% growth in the number of foundations in the US. However, the growth of donations has been relatively slow. Adjusting for inflation, private charitable giving remained steady at $290.89B between 2000 and 2010.[2] With decreasing government support and the slow growth of donations, competition for scarce resources among nonprofit organizations has become intense (Foster and Meinhard 2002; Sargeant and Woodliffe 2007; Thornton 2006). Nonprofits have to spend substantial resources in donor acquisition activities, with about half of the newly acquired donors lost after the first donation (Magson 1999; Masters 2000; Sargeant and Woodliffe 2007). For instance, in the higher education sector, the retention rate for first time donors has been below 30% in 2012 and 2013.[3] Thus, building long-term relationships with donors becomes critical for nonprofits. To combat this challenge, many nonprofits now keep donor-level information that can be leveraged for donor selection and optimal resource allocation (Kumar and Petersen 2005; Lemon, White, and Winer 2002).

This raises an interesting question about whether strategies to manage customer relationships in the for-profit sector can be easily translated as strategies to manage donors in the nonprofit sector. While the data collection process is similar (i.e. recording transactions, marketing efforts, and customer/donor characteristics), the motivations of donors to give varies significantly from the motivations of customers to purchase (Ariely and Norton 2009). However, there are not been

[2] National Center for Charitable Statistics (NCCS) data, available at: http://nccs.urban.org/statistics/index.cfm

[3] https://www.blackbaud.com/nonprofit-resources/highered-fundraising-index

much research into repeat giving behavior by donors to nonprofit organizations. Thus, it is important to understand how acquisition and retention strategies impact sustained giving.

An approach observed specifically in the non-profit industry to motivate sustained giving is to give donors control over how their gift is utilized by the nonprofit. In fact, many nonprofit organizations now offer multiple causes, initiatives, or areas where donations can be directed. The American Red Cross and UNESCO have been using this strategy for a while, and many companies now run cause-related marketing campaigns with multiple causes from which donors can choose. Providing donors with the opportunity to direct their gift toward specific causes or fundraising projects is driven by management beliefs that such options can help increase donation intentions and donor retention. Anecdotal evidence seems to corroborate this belief. Survey studies show that consumers have greater interest in participating in cause-related campaigns that allow donors to choose a charity they want to support.[4] Lab experiments also show that targeting donations has a positive effect on gift amount (Li et al. 2013; Robinson, Irmak, and Jayachandran 2012). However, there is no research which explores the drivers and consequences of a donor's decision to support multiple initiatives at a nonprofit organization.

We focus on this phenomenon of giving to multiple initiatives in our research and empirically test if donors who support multiple initiatives of a nonprofit organization are in fact more valuable over time. We measure the depth and breadth of giving by a donor using a single individual- and time-varying metric we call *Donation Variety*. We define *Donation Variety* as the weighted sum of the share of each initiative a donor supports, where the weight for each initiative is the logarithm of the share (similar to the measurement of entropy).

[4] For instance, 73% of respondents in survey said that they would be more likely to participate in a cause marketing program if they were allowed to choose which charity is selected in-store. Source: http://www.dowelldogood.net/

Our research has three main research questions. In the first study, we focus on answering the first two research questions. In order to answer these first two research questions, we analyze twenty years of donation history of a nonprofit organization. To start, we want to better understand what motivates donors to increase the depth and breadth of their support of a nonprofit organization (i.e. increase *Donation Variety*). We expect that the factors which drive *Donation Variety* are likely to change over the course of the donor's relationship with the nonprofit organization (from acquisition through retention). Thus, our first research question is:

1. *What factors motivate donors to increase the depth and breadth (Donation Variety) of their support of a nonprofit at different stages of their relationship life cycle?*

We find in general that a donor's ties to the nonprofit are more influential in driving *Donation Variety* at the acquisition stage. However, as the donor-nonprofit relationship develops over time (during the retention phase), marketing efforts from the nonprofit organization become more influential at driving *Donation Variety*. In the second part of the first study, we want to understand the impact that *Donation Variety* has on a donor's future giving behavior. Specifically, our goal is to empirically test, after controlling for the other key drivers of giving behavior, how the distribution of past gifts among multiple causes (*Donation Variety*) affects the future giving behavior of a donor. Thus, our second research question is:

2. *What is the effect of the depth and breadth of past gifts (Donation Variety) to a nonprofit on future donor giving behavior?*

We find that after we control for marketing efforts, donor's ties to the nonprofit, and amount of past gifts, the higher the *Donation Variety* of the past donations: (1) the more likely the donor will give again in the next fiscal year, and (2) conditional on a gift occurring, the larger the expected value of the gift. Further, we find empirical evidence that *Donation Variety* also lowers a donor's responsiveness to declining macroeconomic conditions.

In the second study, we further explore the causal relationship between marketing actions and *Donation Variety* through a field study with the focal nonprofit organization. The goal is to understand how changes in the marketing communications by the nonprofit organization can induce different levels of *Donation Variety*. Through this field study we aim to answer our third research question:

3. *Can nonprofit organizations use targeted marketing efforts to encourage donors to increase their Donation Variety?*

We find through our field study that marketing communications that encourage donating to an additional initiative were able to significantly increase the probability of a donor giving again in the future and, conditional on the gift, giving more in total. Further, we found that when donors who already give to multiple initiatives (n = x) are encouraged to give to another initiative (n = x+1), these donors were just as likely to give again as donors in the control group, but the total amount of giving was higher.

We believe that the results of our study provide several key contributions to the nonprofit and marketing literature and practice. Targeted (or directed) giving (i.e. allowing donors to target their gift to specific causes) has recently received some attention in the literature. However, there is need for more research in this area. A review of studies (see Appendix 2.A) shows that most of studies focus on the effectiveness of targeted giving focus on whether giving donors the choice to direct gift affects giving behavior. These studies are mostly in an experimental setting or a small-scale field study. In such settings, choice of causes is limited and the long-term impacts of targeted giving have not been investigated. To the best of our knowledge, our study is the first study in the area of targeted giving that uses donation data at the individual donor level to investigate targeted giving behavior over long-run. Unlike previous studies, we do not focus on whether targeted giving is effective. We consider what motivates donors when they are given the choice of multiple causes to direct their gifts and how this decision to spread gift across causes affects the donor's future giving to that nonprofit. We also take advantage of field study to provide causal evidence that marketing efforts by nonprofit organizations can encourage donors to give to multiple causes and give more to the nonprofit.

The rest of this paper proceeds as follows. First, we discuss theoretical foundation and hypotheses and define *Donation Variety* and illustrate its measurement. Then, we empirically test what factors drive donors to increase *Donation Variety* and the consequences of *Donation Variety* of past gifts on future giving behavior. Next, we describe and provide results of a field study we ran with the focal nonprofit organization. Finally, we discuss the implications along the limitations and opportunities for further research.

Study 1: Drivers and Consequences of Donation Variety

From an exchange process perspective, the ongoing relationship process between the nonprofit organization and the donor follows steps similar in nature to the firm-customer exchange process outlined by Gupta and Zeithaml (2006). First, the nonprofit organization communicates with potential donors to acquire them through various marketing efforts. Second, the potential donors make a set of simultaneous decisions on: (1) whether to donate and conditional on donating, (2) how much to donate, and (3) how to allocate the donation to different initiatives. A donor's decision on whether to give, how much to give, and to which donation options to allocate the gift is affected by the donor's ties to the nonprofit (i.e. personal experience, level of identification with and interest in different donation options), donor's characteristics, and the nonprofit-initiated marketing efforts. After the nonprofit receives the donations in the given time period, the nonprofit-donor exchange process then repeats dynamically over time as the relationship between the two continues to develop.

Nonprofits that offer multiple donation options hope that this strategy increases donation intentions and donor retention. Giving choices to donors increase a donor's perception of having a personal role in helping a nonprofit organization. This facilitates development of role identity by creating a sense of "self-determination" and "ownership," and allows donors to contribute in personally meaningful ways (Grant 2012). In experimental settings, giving donors control to choose between multiple programs offered by a charity increased both donation amount and purchase intention for the associated products (Null 2011; Robinson, Irmak, and Jayachandran 2012). Despite the prevalence of multiple-cause donation, there is little empirical research on whether giving to multiple causes increases the donor's repeat giving behavior to the nonprofit and what factors may motivate a donor to distribute her gift across multiple causes (Bennett 2012; Ly and Mason 2012).

Literature on variety in consumption of goods and services suggest that a consumer may seek variety because of satiation with current options or need for novelty (Kahn 1995; McAlister and Pessemier 1982). However, when a donor makes a gift, she sacrifices her own "physical consumption" to get satisfaction from trading off "positive physical consumption" for "positive conceptual consumption" (Ariely and Norton 2009). This suggests that the process of giving to charities is conceptually different than that of consuming goods or services and what motivate donors to support multiple causes might be different from what motivate variety seeking in consumption. The literature on variety seeking also does little help to hypothesize the effect of supporting multiple causes on a donor's giving behavior to a nonprofit. Therefore, we draw on the literature on tie-strength (Granovetter 1985; Uzzi 1996) and social capital theory (Coleman 1988; Putnam 1995) to hypothesize the factors that explain drivers and consequences of giving to multiple causes.

Hypothesis Development

Drivers of Donation Variety. First, we would like to explore what factors influence a donor's decision to support multiple causes of a nonprofit. Similar to customer-firm relationship, both internal and external motivators may impact a donor-nonprofit relationship. Individual are intrinsically motivated when they get inherent satisfaction and enjoyment from their act. Intrinsic motivators are thus "an endogenous part of a person's engagement in the activity". Extrinsic motivations on the other hand come from an outside source and encourage individual to obtain a desired outcome (Amabile 1993; Ryan and Deci 2000). A donor's engagement with a nonprofit may internally drive the donor's decision to support multiple causes of the nonprofit. For instance, a donor who has personal interest and experience with different causes may feel more broadly tied to the nonprofit than a donor who is mainly interested in fewer causes and focuses her support on those causes. In addition, nonprofit-initiated marketing efforts are an external motivator for a donor to support multiple causes. Given that the context of charitable giving is highly relationship-based, we investigate how these two key factors (intrinsic vs. extrinsic) affect donation variety in two stages of a donor's life cycle (acquisition vs. retention).

Intrinsic Motivators. Individuals may engage in an activity because of an inherent desire. Donors often prefer to give to charities that they can inherently relate to. Personal experience with a charity, whether a donor has benefited from a cause in the past or believes that will benefit from it, motivates giving to that charity (Ariely and Norton 2009; Bennett 2010; Bekkers and Wiepking 2007; Null 2011; Robinson, Irmak, and Jayachandran 2012). Research on philanthropy also shows that many people prefer to support those who are similar to themselves and help charities that are congruent with their identification (Bennett 2012; Sargeant and Woodliffe 2007). Identification in this context refers to the extent to which donors feel connected with a specific cause and how those causes align with internal fit (i.e. causes that are closer to their heart) (Aaker and Akutsu 2009; Sirgy 1982). Thus, a donor who has a personal experience or identifies with multiple causes of the nonprofit is more likely to support multiple causes.

When a donor makes her first gift to a nonprofit organization, she may have limited knowledge about the various donation options offered by the organization. In addition, at the early stage of relationship, individuals have less confidence in their evaluation of an organization's offerings and might feel uncertain about the way in which the nonprofit provides value to the recipients of various causes (Bolton 1998; Swann and Gill 1997; Verhoef, Franses, and Hoekstra 2002). Thus, at the initial stage of relationship (acquisition), donors are more likely to make donation choices based on their personal experiences with specific causes and degree of identification with a cause (internal motivators). And, a donor who can relate to multiple causes initially is more likely to give to multiple causes for her first donation compared to a donor who is initially tied only to a single or few causes. Thus, we hypothesize:

H1: The positive effect of a donor's intrinsic motivators on Donation Variety is stronger in the acquisition phase than the retention phase.

Extrinsic Motivators. Individuals may engage in an act because of an external source that motivates them to obtain a desired outcome. Donors may be driven to donate by external motivators, in this case ongoing marketing communications between the foundation and the donor. Like customer loyalty, donor loyalty requires appropriate communication and a relationship-building strategy. If donors are "neglected and not asked for a second gift," their contributions might decrease or even stop after a first donation (Andreoni 2006; Bekkers and Wiepking 2007; Sargeant 2001). Nonprofits that give feedback to donors by expressing appreciation and/or by responding to donor concerns can impact a donor's attitudes toward the organization and their willingness to engage in repeat giving (Bekkers and Wiepking 2007; Kottasz 2004; Sargeant 2001).

Marketing efforts such as loyalty programs and direct mails have positive effect on cross-buying of additional products and services (Kumar, George, and Pancras 2008; George, Kumar, and Grewal 2013; Verhoef, Franses, and Hoekstra 2001; Li, Sun, and Montgomery 2011). Likewise, nonprofits can leverage targeted marketing techniques to develop more relationship with donors, provide information about organization's various causes and programs, and introduce donors to new donation opportunities. Further, as the donor-nonprofit relationship grows over time, the donor develops more trust toward the nonprofit and its ability to provide value to the recipient of donation. This trust influences them to give to more causes they are aware of from marketing communications even if they don't have prior ties with the causes. As a result, we expect that over time, the donor becomes more receptive to the nonprofit's communications and solicitation requests to support additional causes (Celsi and Olson 1988). Thus, we hypothesize:

H2: The positive effect of extrinsic motivators on Donation Variety is stronger in the retention phase than the acquisition phase.

Consequences of Donation Variety. Main effect of Donation Variety: Charitable organizations can often enhance donation intentions by granting donors choices for which causes they wish to support. Donors who support multiple initiatives build a more extended network with the nonprofit organization. In commercial context, social capital, measured as the strength of the buyer-seller tie, has significant positive impact on purchase behavior (Frenzen and Davis 1990). Social capital theory posits that a donor who is connected to multiple causes of a nonprofit has stronger social ties to the nonprofit through her multiple connections (Putnam 1995). Stronger ties to the nonprofit through involvement with multiple causes of a nonprofit can reinforce a donor's contribution to the nonprofit (Apinunmahakul and Devlie 2008; Brooks 2005; McAdam and Paulsen 1993, Brown and Ferris 2007). In addition, people with more diverse and extended social networks are more exposed to donation and volunteering solicitations and may have lower cost of giving (Brown and Ferris 2007; Uzzi 1999). As a result, a donor with more extended network with a nonprofit may gain higher perceived utility from her gift to the nonprofit, and in turn she is expected to make more donations in future. Thus, we expect the incremental benefits from a more extended donor-nonprofit network to be more valuable than the gain from a donor-nonprofit relationship that focuses on fewer causes.

In addition, giving repeatedly to a single initiative might lead to a decrease in marginal warm-glow utility derived from the act of giving. This in turn decreases a donor's willingness to give in the future (Andreoni 1990). In an experimental study, Null (2011) show that warm glow utility of giving can lead to "a love of variety" among charities. In her experiment, most participants give simultaneously to multiple charities even when charities are similar in mission, and even when the benefits of the gift to the recipient were set at different levels by varying matching rate. We expect that giving to a variety of causes increase the marginal utility and total satisfaction a donor experiences from giving to a nonprofit organization. Satisfaction and positive evaluation of an experience leads to repeated engagement with that experience (Bennett 2012; Grant 2012). We argue that after controlling for a donor's amount of past gift and a donor's capability of giving, donors who have previously distributed their gift across more donation options (i.e. higher *Donation Variety*) will give more in future. Thus, we hypothesize:

H3: All else being equal, individuals who have higher Donation Variety are expected to give more in the future than individuals with a lower Donation Variety.

Moderating effect of Donation Variety on economic shocks. Economic shocks have a significant impact on a donor's ability and desire to make a donation. As the economic condition declines and purchasing power decreases across all individuals, people start to cut down on unnecessary costs. For instance, during the recent economic downturn in the US, the percentage of consumers involved in a nonprofit cause dropped from 60 to 53 percent within two years.[5] The uncertainties of economic shocks have a significant impact on a nonprofit's ability to predict future donor value. During an economic downturn the cost of giving increases, and all donors face a declining budget requiring some costs to be cut. In such situations, donors with weak ties to the nonprofit may be more willing to cut their support to a charity that they do not feel strongly tied to. However, donors with strong ties to the nonprofit may be more willing to tradeoff on some of their other costs to keep up with support. Donors with strong tie the nonprofit have internalized a donor role into their identity and feel more committed to sustain their support even when economic conditions decline (Brown and Ferris 2007; Seargant and Woodliffe 2007). Thus, we hypothesize:

H4: As the macroeconomic climate declines, individuals with a higher Donation Variety will respond less negatively than donors with a lower Donation Variety.

Data

Context. We chose a university foundation as the context to empirically test our hypotheses. Donations to educational organizations are of great importance. In the United States, education organizations receive the second-largest share of all charitable contributions.[6] Higher educational

[5] http://www.causemarketingforum.com

[6] http://www.givingusareports.org

organizations are greatly dependent on contributions of alumni donors. Further, the ability to acquire and retain alumni donors is a major challenge for higher educational organizations. Despite the economic growth after the great economic recession, the declining acquisition rate of new alumni donors is a threat for survival of higher education organizations. Another major challenge for educational institutions is a low retention rate, especially since the majority of donors are lost after their first gift.[7] Thus, understanding a donor's behavior and motivations for sustained support is of great importance for educational organizations.

Further, educational foundations allow donors to give to multiple units. Within a college or university, donors can choose to either generally donate to an unrestricted fund to be used at the foundation's discretion, or the donor can choose to make a donation which is targeted to specific departments, associations, scholarships, memorials, etc. To motivate our econometric model, we run an exploratory analysis on the donation data of a major public university foundation to see whether there is a difference between the ongoing giving behaviors of donors who give to one initiative versus those who give to multiple initiatives.

For our analysis, we use the donor database of a major public university foundation. The focal university has 44 specific departments and associations where donors can direct their donations, including, but not limited to, funds for specific colleges, schools, groups, scholarships, memorials, as well as a general unrestricted fund. We focus only on donors from the annual giving program and exclude donors involved in or targeted for major planned and capital gifts. Planned gifts and capital gifts are one time large gifts that are often at or near the end of the relationship (e.g. bequests) or dedicated to special projects (e.g. scholarships,

[7] Annual Report on Higher Education Alumni Giving, 2013. Source: https://www.blackbaud.com/nonprofit-resources/highered-fundraising-index

buildings). These major gifts are only made by a small segment of donors. On the other hand, the majority of donors participate in the annual giving program. Annual gifts are smaller gifts that require yearly decision-making by donors. We believe these recurring gifts offer a good representation of the ongoing relationship between most donors and nonprofit organizations.

Sampling. We use a stratified random sample of 500 donors in the annual giving program that made their first gift in each of the years between fiscal year (FY)[8] 1993 and FY 2003 and record each individual's characteristics and donation behavior aggregated at the annual level through the end of FY 2012. This gives us a sample of 5,500 donors (500 for each year) with an average of 15 years of data for each donor. In our dataset, each donation is on average around $381, the total donations per donor over the observation window are about $2,391, and the total number of gifts in the observation window is about 11.2 per donor. 96% of donors made their initial donation to a single initiative leaving only about 4% who donated to more than one initiative in the first year. By the end of FY 2012, 67% of donors gave to multiple initiatives. This means after the initial gift, a majority of donors gave to new initiatives in a subsequent year.

Variable Operationalization

Donation Variety. The key variable we use in our model is *Donation Variety*. We propose that, in addition to the number of different initiatives an individual donates to, it is important to measure the strength of the ties a donor builds with a nonprofit through supporting multiple initiatives. Therefore, we introduce the variable *Donation Variety* to differentiate various donation patterns. Here, we define the *Donation Variety* for a given donor as the weighted sum

[8] Fiscal Year (FY) for this nonprofit organization starts on July 1st and ends on June 30th

of the share of each initiative a donor supports, where the weight for each initiative is the logarithm of its share. Thus, *Donation Variety* can be represented as:

$$\text{Donation Variety}_{it} = \left| \sum_{j=1}^{m} S_{ijt} \ln S_{ijt} \right| \tag{1}$$

At a given point in time t for donor i, S_{ijt} is the share of the total donation donor i made to initiative j until time t relative to the total donation donor i made to the nonprofit organization until that time. For a donor who gives exclusively to a single initiative, *Donation Variety* is 0. The *Donation Variety* increases as a donor gives to more initiatives and gives evenly across many different initiatives. *Donation variety* is a cumulative measure of giving behavior that takes into account both the number of initiatives an individual selects for donation and the relative importance of each initiative in the total amount of donation. This measure gets updated every time a donor makes a new donation to reflect the change in the giving portfolio.

The *Donation Variety* index is similar to the entropy measure that is used to measure the level of diversity in a company's business portfolio as well as in an individual's investment portfolio (e.g. Chatterjee, and Blocher 1992; Hoskisson, et al. 1993; Palepu 1985; Palich, Cardinal, and Miller 2000; Woerheide and Persson 1993). Entropy measure has also been applied by marketing scholars to model customer brand preferences using market share of various brands (Herniter 1976; Kapur, Bector, and Kumar 1984). Similarly, Simonson and Winer (1992) applied a variety score based on the overall share of items purchased by household to account for choice variety. The authors also used the sum of the squares of the brands' shares to measure "taste concentration" (homogeneity) in a household's purchase portfolio. Further, Kahn (1995) recommends the use of entropy measure to account for variety in a consumer's purchase portfolio. Kahn (1995) argues that: "even if the number of items included in the choice set is constant, there is more variety in the choice history if the choice shares of the items included are equal (maximum entropy) than if one alternative dominates (low entropy)." Thus, we apply a similar measure to measure the depth and breadth of a donor's giving to multiple donation options. We argue that, compared to other possible measures such as average donation per initiative or number of initiatives chosen for donation, *Donation Variety* is a more informative measure of how donors distribute their donations across multiple initiatives.

Intrinsic Motivators. To test H1 we need a variable (or set of variables) which represents the extent to which a donor has an intrinsic motivation to donate to multiple initiatives. We expect that a donor's strength of ties to various initiatives of a nonprofit can act as a good indicator of a stronger tie and broad connectedness to the university. Sharing demographic characteristics has been shown as a good proxy for measuring the strength of a tie between two individuals (Reagans 2005). Thus, we expect that variables which describe cases where alumni likely have multiple connections with different initiatives/departments of a university are good indicators of stronger and broader intrinsic ties to the university. Thus, we use two variables as indicators of the strength and breadth of ties across different initiatives/departments: (1) the number of degrees the alumnus has with the university, and (2) having a spouse that also graduated from the university. We expect that these two variables are likely indicators of alumni that have had or shared broader experiences across the university. For example, donors with multiple degrees have often had different experiences across programs (e.g. Bachelors, Masters, PhD) or across schools (e.g. Arts & Sciences, Business, Medicine, Engineering, Law, etc.). We find that the alumni of the university have on average about 1.2 degrees from the university and about 30% are married to other alumni from the university.

Extrinsic Motivators. To test H2 we need a variable (or set of variables) which represents the extent to which a donor has an extrinsic motivation to donate to multiple initiatives. Much of the external motivation for alumni to make donations comes from the marketing efforts which are initiated by the university foundation. These marketing efforts initiated by the university foundation include personal visits, phonathon calls, invitations to events, and direct mail/email solicitations. We expect that different types of marketing efforts are likely to have varying impacts on a donor's decision to make a gift. For reasons of parsimony, we choose to group phonathon calls and direct mail/email as impersonal marketing efforts, since the message content used for these marketing efforts is homogenous across the donor population and less interactive. Further, we group personal visits and invitations to events as personal marketing efforts, since their content and experience is richer and more donor-specific (Venkatesan and Kumar 2004).

In our sample, on average, alumni receive about five times as many impersonal (0.49) vs. personal (0.09) marketing communications from the university per year. This is common, given the much higher cost of personal marketing communications. We note that the focal educational foundation follows a similar process when initiating any type of marketing communications to alumni. All alumni generally receive a communication from both the university and the general alumni association starting just prior to graduation. All communications, including informational newsletters, contain an appeal letter asking for a gift. These communications generally continue for several years post-graduation, regardless of whether a gift is given. When an initial gift is given, the alumnus can choose whether the gift is given to a specific initiative, multiple initiatives, or to an unrestricted fund.[9] Once a gift is given, the initiative(s) supported often communicate regularly with the donor in the future asking for subsequent gifts to the same initiative(s) which were previously supported.

[9] We note that an unrestricted gift is also an initiative a donor can give to, just like a gift to a specific department.

Gift Giving Behavior. To test H3 we need a variable which represents the outcome of the gift giving process. In this case, since we aggregate the data on an annual basis by fiscal year, we define gift giving as the total amount of donations by a given donor in a given year. We find that conditional on giving, the average gift amount is about $381. We also control for the recency effect of gift giving by including lag of donation amount in our analysis.

Macroeconomic Condition. To test H4 we need a variable which represents the macroeconomic conditions that the alumni are facing. Similar to many other studies in marketing, we measure the overall macroeconomic condition as the cyclical component of GDP data after we apply a HP-filter (Hodrick and Prescott 1997) to remove the long-term trend component of GDP. Thus, the average macroeconomic condition in the sample is 0 and any deviation above (below) 0 suggests a positive (negative) macroeconomic climate.

Control Variables. In addition we include several control variables in our model. We include variables that try to capture the financial strength or capacity of giving of a given alumnus. First, we include the average household income and average charitable contribution at the zip-code level based on the donor's residence. Second, we include time since graduation since the longer it has been since an alumnus graduated, the higher the likelihood that their earning power and assets are higher. Finally, we control for the amount of the previous gift. We also include some demographic variables to account for observed heterogeneity. These include gender and location (in-state vs. out-of-state). We provide a list of the variables, descriptive statistics, and description of the operationalization of each variable in Table 2.1 (See Table 2.1)

<u>Model Development</u>

Model Free Evidence. For the first step of our model development we run an exploratory analysis to provide some model free evidence of how donation variety might be related to donor value. We use the same sample of 5,500 donors in the annual giving program of a public university which made their initial gift to a single initiative between fiscal year (FY) 1993 and FY 2003. We split the sample into two groups: (1) donors who began at some point to give to multiple initiatives (n = 3,720), and (2) donors that only give to a single initiative during the entire observation window (n = 1,780) through FY 2012. For the first group (labeled Multiple Initiatives), we split the data into the time period when the donors only gave to a single initiative and the time period after they began giving to multiple initiatives. We then determine the average gift amount for donors before ($149.34) and after ($500.16) giving to a second initiative. For the second group (labeled Single Initiative), we split the data into two time periods as well. Here, we treat the first five years as early gifts (as this is the average time that a donor in the first group waits before donating to multiple initiatives) and any time after five years as later gifts. We then determine the average gift amount for donors in the early ($114.03) and later ($194.20) time periods (See Figure 2.1).

First, we see that in both cases the average gifts in the early time period are lower than the average gifts in the later time periods, suggesting that, over time, there is an increase in average giving for all donors. However, we see that the increase in average gift amount for donors who give to multiple initiatives is significantly larger than the increase for the single-initiative donors ($270.65; $p < 0.01$). This provides some evidence that increases in *Donation Variety* lead to increases in giving amounts. However, it is also important to quantify the benefits of *Donation Variety* by controlling for as many other factors that may affect donations as possible. To do this we build an econometric model which can identify the antecedents and consequences of *Donation Variety*.

Endogeneity of Marketing. To empirically test our hypotheses, we must first control for the endogeneity of marketing efforts, since nonprofit organizations usually do not send solicitations at random. Nonprofit organizations commonly focus their fundraising efforts on donors and prospects that have a higher likelihood of donation or belong to specific demographic segments. To address the issue of endogeneity with marketing efforts, we use instrumental variables and estimate the instrumental variable model for both personal and impersonal marketing efforts and use a control function approach (Petrin and Train 2010) to include marketing efforts (both personal and impersonal) into the next step of analysis, along with the computed error from the instrumental variable equations. The detailed discussion on instrumental variable model and estimations is provided in Appendix 2.B (See Appendix 2.B)

Methodology. In order to test hypotheses H1 and H2, we need a model that can help us understand what factors motivate a donor to increase donation variety over the donor's lifecycle. To accommodate both the acquisition and retention stages of donor relationship in the model, we use a binary variable ($First_{i,t}$) to distinguish between initial and subsequent gifts, where $First_{i,t} = 1$ when it is the initial gift of donor *i* at time t, and $First_{i,t} = 0$ when it is a subsequent donation by a given donor *i*. For $First_{i,t} = 1$, the interaction of $First_{i,t}$ with donor intrinsic motivators and nonprofit-initiated marketing efforts help us to identify whether the impact of donors intrinsic and extrinsic motivators are strengthened or weakened across acquisition and retention stages.

The focal variable of interest in this model is *Donation Variety*, as measured in Equation 1. *Donation Variety* is censored at 0 for donors who exclusively support a single initiative. Further, there is likely a high inertia in the measure of *Donation Variety* as it is measured as a cumulative index. To address the issue of the potential serial correlation of *Donation Variety*, we estimate a dynamic panel model with unobserved heterogeneity with *Donation Variety* as the dependent variable. As noted, we do not observe a positive *Donation Variety* for all donors. In fact, most donors do not give to multiple initiatives in their initial gift (> 95% give to one initiative on their first gift), and some donors never actually give to multiple initiatives (about 33% never give to multiple initiatives). Therefore, our model needs to handle the partial observability of *Donation Variety* (i.e. it is censored at 0). To do this we estimate the following panel data model:

$$\text{Variety}_{i,t_i}^{*} = x_{i,t}\beta_1 + c_i + \mu_{i,t}$$

$$\text{Variety}_{i,t} = \begin{cases} \text{Variety}_{i,t_i}^{*} & \text{if Variety}_{i,t_i}^{*} > 0 \\ 0 & \text{if Variety}_{i,t_i}^{*} = 0 \end{cases} \tag{2}$$

Where $\text{Variety}_{i,t}$ is the *Donation Variety* for donor i up to time t as computed from Equation 1 (for t = 1, 2, …, T), X_{it} contains individual and time-varying explanatory variables such as intrinsic and extrinsic motivators, lagged donation amount, lagged donation variety, and first year dummy and its interaction with both intrinsic and extrinsic motivators; c_i and $\mu_{i,t}$ are individual-specific unobserved effect and normally distributed idiosyncratic error term. The limited dependent variable model is generally fitted using Tobit specification. One of the key limitations of Tobit specification is that the underlying process driving the probability of observing a positive value [$P(Variety_{i,t}>0|X_{it})$] and the actual value [$E(Variety_{i,t})|Variety_{i,t}>0, X_{it})$] are both driven by the same underlying process. We adopt a general class of model specification proposed by Cragg (1971) that integrates the Probit and truncated normal models:

$$f(d_{it}, \text{Variety}_{i,t} \mid Z_{it}, X_{it}) = \{1-\Phi(Z_{it}\gamma)\}^{1(d_{it}=0)} \left[\Phi(Z_{it}\gamma) 2\pi^{-\frac{1}{2}} \sigma^{-1} \frac{e^{\left\{-(\text{Variety}_{i,t} - X_{it}\beta)^2/2\sigma^2\right\}}}{\Phi(X_{it}\beta)/\sigma} \right]^{1(d_{it}=1)} \tag{3}$$

where $d = \begin{cases} 1 & \text{if Variety}_{i,t} > 0 \\ 0 & \text{if Variety}_{i,t} = 0 \end{cases}$. Unlike Tobit model specification, the Cragg model permits:

(a) different explanatory variables for each decision, i.e. $Z \neq X$; and (b) even when $Z = X$; the underlying process driving the two decisions could be different, whereas in Tobit model $\gamma = \beta/\delta$. Please note that Tobit model is a special form of Cragg model in which $Z = X$ and $\gamma = \beta/\delta$. Thus, Cragg model is a more flexible alternative to Tobit model and it also has the benefit of enhanced efficiency due to the simultaneous estimation of both stages. We estimate the Cragg model specification using a maximum likelihood-based Craggit procedure in STATA 13.1 (Burke 2009). We use clustered standard errors to account for autocorrelation and panel-specific heteroskedasticity.

Similarly, to test hypotheses H3 and H4 we need a model that can accommodate partial observability of the dependent variable, gift amount (i.e. we only observe a value for gift amount when a donation occurred). The model takes the following format:

$$\mathrm{Ln}(\mathrm{Gift}_{i,t})^{*} = x_{i,t}\beta_1 + c_i + \mu_{i,t}$$

$$\mathrm{Ln}(\mathrm{Gift}_{i,t}) = \begin{cases} \mathrm{Ln}(\mathrm{Gift}_{i,t})^{*} & \text{if } \mathrm{Ln}(\mathrm{Gift}_{i,t})^{*} > 0 \\ 0 & \text{if } \mathrm{Ln}(\mathrm{Gift}_{i,t})^{*} = 0 \end{cases} \tag{4}$$

where $\ln(\mathrm{Gift}_{i,t})$ is the log of the gift amount given by donor i at time t (for t = 1, 2, …, T), and X_{it} contains individual and time-varying explanatory variables such as lagged donation amount, lagged donation variety, marketing efforts and donor's intrinsic motivators; c_i and $\mu_{i,t}$ are individual-specific unobserved effect and normally distributed idiosyncratic error term. We use the same maximum likelihood-based Craggit procedure (Burke 2009) to estimate the model in equation (5).

$$f(d_{it}, \mathrm{Ln}(\mathrm{Gift}_{i,t}) \mid Z_{it}, X_{it}) = \{1 - \Phi(Z_{it}\gamma)\}^{1(d_{it}=0)} \left[\Phi(Z_{it}\gamma) 2\pi^{-\frac{1}{2}} \sigma^{-1} \frac{e^{\left\{-(\mathrm{Ln}(\mathrm{Gift}_{i,t}) - X_{it}\beta)^2/2\sigma^2\right\}}}{\Phi(X_{it}\beta)/\sigma} \right]^{1(d_{it}=1)} \tag{5}$$

where $d = \begin{cases} 1 & \text{if } \mathrm{Ln}(\mathrm{Gift}_{i,t}) > 0 \\ 0 & \text{if } \mathrm{Ln}(\mathrm{Gift}_{i,t}) = 0 \end{cases}$.

Results

The results of estimation for Equations 3 and 5 are presented in Table 2.2. Both models have good fit and majority of coefficients are statistically significant. However, interpretation of coefficients in the Cragg model can be precarious, as the effect of an independent variable can vary in magnitude as well as direction across the Probit model and the truncated normal regression. The problem of interpretation of coefficients associated with interaction effects in non-linear models is even more complicated (Ai and Norton 2003). Thus to empirically test the hypotheses, we calculate the unconditional expected value of the dependent variables (i.e. *Donation Variety* and donation amount) at each time t. We can then compare the mean of the predicted values across the different groups we want to test (See Table 2.2)

To interpret the effect of intrinsic and extrinsic motivators on driving *Donation Variety*, we estimate the expected *Donation Variety* at different levels of intrinsic and extrinsic variables for both acquisition (first gift) and retention (repeat gift) stages of donor-nonprofit relationship. Estimations are presented in Figure 2a to 2d. Figure 2a and 2b present the interaction effect of intrinsic motivators and first donation indicator. These figures show that a donor's multiple ties to the nonprofit are more influential on driving *Donation Variety* at the initial stage of the donor-nonprofit relationship than the retention stage. For first gift, donors who have multiple degrees from the university (Figure 2a) and donors whose spouse are also university alumni (Figure 2b) are more likely to have a higher *Donation Variety* than donors who have fewer different ties to the university. However, we also notice that in the retention phase the donor's intrinsic motivators have no additional effect on *Donation Variety* (See Figure 2.2a and 2.2b).

Figure 2c and 2d present the interaction effect of marketing efforts and first donation indicator (See Figure 2.2c and 2.2d). These figures show that nonprofit marketing efforts are more influential in driving *Donation Variety* at the retention stage than the acquisition stage. For first gift, marketing seems to play small role in encouraging donors to give to increase *Donation Variety*. However for repeat gifts, donors who receive more marketing efforts from the university foundation have higher expected *Donation Variety* on average as compared to donors who receive fewer marketing efforts.

In order to estimate the direct and moderating effect of *Donation Variety* on gift amount, we predict the expected gift amount given different levels of *Donation Variety*. For donors who give to only one initiative, *Donation Variety* is 0 (no variety). For donors who give to multiple initiatives, we use median split to group them as donors with a low level of Donation Variety (0 < *Donation Variety* < 0.64) and with a high level of *Donation Variety* (*Donation Variety* >= 0.64). To test the direct effect of Donation Variety on gift amount, we compare the difference in average expected gift amount across donors with low and high levels of Donation Variety. The average expected gift size is $115.62 for donors who give to only one initiative. The average expected gift amount for donors with low and high levels of Donation Variety is $394.76 and $795.80, respectively. These results indicate a significant and positive direct effect of Donation Variety on gift amount.

Next, we test the interaction effect of *Donation Variety* and macroeconomic condition (See Figure 2.3a). Economic conditions below and above the trend line derived from the HP-filter are classified as negative and positive economic conditions, respectively. As it is shown in Figure 2.3a, as economic condition declines, donors decrease their financial support for the university foundation.[10] However, the decrease in financial support is much greater for donors who give to a single initiative than donors who give to multiple initiatives.

While we do not formally hypothesize the moderating effect of *Donation Variety* on marketing efforts, we still include the interaction between the two marketing variables and *Donation Variety* to control for the potential impact of marketing efforts by the university foundation. We want to see whether there is some evidence that donors with different levels of *Donation Variety* tend to respond differently to marketing efforts (both impersonal and personal) by the university foundation (See Figure 2.3b and 2.3c). Figure 2.3b shows the interaction of *Donation Variety* and impersonal marketing costs. As it is shown, donors who receive more impersonal marketing efforts make larger gifts as compared to donors who receive fewer impersonal marketing efforts. The difference in average gift size for the two groups becomes larger as donors give to a more varied portfolio of initiatives. Figure 2.3c shows the interaction effect of *Donation Variety* and personal marketing effort. Given that the majority of donors receive no personal marketing effort, we split donors into two groups: donors who receive no personal marketing, and donors who receive some personal marketing. Figure 2.3c shows that personal marketing effort is mostly targeted at high-value donors. However, we can see that the difference in average gift size for donors who receive some marketing and donors who receive no marketing becomes much larger for donors with higher levels of *Donation Variety*.

[10] We note that the focal university does not alter its marketing budget in accordance with changes in macroeconomic condition (i.e. the budget does not increase (decrease) in good (bad) macroeconomic conditions).

Comparing Donation Variety with Breadth and Depth of Donations

Further, we want to see whether our proposed measure of *Donation Variety* (see Equation 1) outperforms measures commonly used to represent the depth and breadth of a customer or donor's relationship with an organization (e.g. Crossbuy and Depth of Buying). In this case, we created 2 variables which represent the depth and breadth of giving: the total number of initiatives supported by donor i up to time t-1 (breadth of giving) and the accumulated amount of gifts by donor i up to time t-1 (depth of giving).We called these two measures cross-donation and total donation. First, we measured the correlation of the *Donation Variety* with these other two measures. The correlation of *Donation Variety* with number of initiatives supported (breadth) and cumulative gift amount (depth) are 0.762 and 0.307 respectively.

This suggests that these variables seem to represent the same construct measuring the depth and breadth in relationship a donor has with a nonprofit organization. However, when we only compare the cases where the *Donation Variety* is positive (i.e. giving to multiple initiatives), the correlations with number of initiatives supported and cumulative gift amount are 0.604 and 0.034 respectively. This seems to suggest that, as the distribution of support to each initiative varies, the measure of *Donation Variety* we use in this study begins to capture subtle differences from the separate measures of the number of cross-donation and depth of donation.

We also want to see the economic significance of the difference in the results when we use the measure *Donation Variety* versus cross-donation and total donation. To do this, we estimate the models from Equations 3 and 5 after substituting cross-donation and total donation for *Donation Variety* (see the results of the estimation in Appendix 2.C). In general, we find cross-donation and total donation are significant in each of the Probit models and in the main model (the same as *Donation Variety*). To test the in-sample model fit differences, we compare the

MAD and MAPE of the expected donation value for all donors in all time periods in the observation window. We find the in-sample MAD (MAPE) for the *Donation Variety* model is $60.11 (17.27%) and for the cross-donation and total donation model is $70.97 (18.38%). This suggests that the model with a single measure of *Donation Variety* captures more of the variation in expected donation amounts than the model with separate variables representing the breadth (cross-donation) and depth (total donations) of donations. Next, we test the out-of-sample fit of the model. To do this, we used the coefficients from the models to select the 'best' donors based on the predicted expected donation in FY 2013, given the original observation window of the data is to the end of FY 2012. We then see if the foundation is better off selecting the top percentiles of donors (10%, 15%, and 25%) based on expected donation from the *Donation Variety* or cross-donation and total donation models (See Table 2.3).

We see from Table 2.3 that, whether the foundation selects the top 10%, 15%, or 25% of donors based on the expected giving amount predicted by the two different models, that the model using *Donation Variety* helps the university foundation select donors with higher giving amounts in FY 2013 by 6.7%, 6.2%, and 5.4% respectively. All of these results suggest that using the proposed measure of *Donation Variety* is more valuable than the traditional (and separate) measures of breadth (cross-donation) and depth (total donation), as *Donation Variety* is a single measure (rather than two independent measures) that captures both the breadth and distribution of depth of donations made to a nonprofit organization.

Discussion

In Study 1 we explored what drives a donor to support multiple initiatives and how the decision made by a donor to support one vs. multiple initiatives has an impact on that donor's future value to the nonprofit organization. We found that at the acquisition stage, donor intrinsic motivations (marketing efforts) are more (less) effective at driving donors to give to multiple initiatives and increasing *Donation Variety*, confirming hypothesis H1 (H2). This suggests that at the acquisition phase, nonprofit organizations should look for donors with the 'right' donor profile (i.e. characteristics that match donors with higher *Donation Variety*) to acquire donors with the highest probability of giving to multiple initiatives in their initial gift. At the retention phase, nonprofit organizations seem to have more influence in getting donors to give to multiple initiatives and increase *Donation Variety*. This suggests that any initiative by the nonprofit organization to influence *Donation Variety* will likely be more effective if applied to donors who have already made gifts (retention) rather than donors who have yet to make a gift (acquisition).

In regard to the effect of a donor's decision to distribute her gifts across multiple initiatives on the donor's future value, we found donors who give to a more varied profile of initiatives in the past to be willing to donate more in the future, confirming H3. Level of *Donation Variety* has a significant positive effect on probability of donation. The average amount of a gift when a donation is made is also almost twice as large for donors who distribute their past donations across more initiatives evenly. We also find that *Donation Variety* has significant moderating impact on the effect of macroeconomic condition on a donor's giving. We found donors with a higher degree of *Donation Variety* are far less affected by the bad economy and their support drops by only 1.84%. In contrast, donors who give to a single initiative, decrease their support by 87.5% as economic conditions significantly decline, confirming H4. Thus, encouraging donors to distribute their support across more initiatives can help nonprofit organizations retain their valuable donors and maintain donation levels even during an economic downturn. Therefore, it is worthwhile for the nonprofit organization to identify what motivates donors to increase the depth and breadth of giving (i.e. *Donation Variety*).

To validate our empirical finding, we run a field study with the focal university foundation of the empirical study to test whether the university foundation can use targeted marketing efforts to influence current donors to increase *Donation Variety*.

Study 2: Field Study

Given that we find that donors with a higher *Donation Variety* are more valuable to the university foundation than donors with a lower *Donation Variety*, we propose a field study to determine the extent to which efforts by the university foundation can be targeted at donors to encourage giving across multiple initiatives. The main benefit of running this field study is two-fold. First, a field study offers strong causal evidence that nonprofit firms can actually motivate single initiative donors to increase their depth and breadth of giving. Second, it can provide a general framework for other nonprofit foundations to motivate donors to increase *Donation Variety*. In our field study, we manipulate the content of direct mail and email appeals from the focal university foundation to motivate single initiative donors to give to multiple initiatives and to motivate donors of multiple initiatives to further increase the number of initiatives supported.

<u>Objective and Setup</u>

Email and direct mail solicitations at this university foundation often ask donors to repeat their donation to the initiative(s) they have supported previously. We want to test whether changing the content of these email and direct mail solicitations can affect *Donation Variety*. We test if highlighting other initiatives in the university that the donor is likely to identify with can encourage *Donation Variety*. We expect that increasing *Donation Variety* should lead to increases in donation probability and total giving amounts by donors who respond favorably to the treated marketing communications.

Method

The field study includes a stratified random sample of 1,200 alumni from the focal university who all graduated with a degree from the business school (undergraduate, MBA, and/or Ph.D.), made at least one donation in fiscal year (FY) 2012, and, as of January 2013, had yet to donate in FY 2013. We took a stratified random sample of donors which fell into one of four groups that include donors who had given: (1) only to the business school in the past (no *Donation Variety*; n=200), (2) to multiple initiatives including the business school in the past (positive *Donation Variety*; n=200), (3) only to one other initiative in the past, not including the business school (no *Donation Variety*; n=400), and (4) to multiple initiatives in the past, not including the business school (positive *Donation Variety*; n=400). We use these four groups so that we can differentiate between the effect of encouraging an alumnus to increase *Donation Variety* and give to schools other than the one they graduated from and the effect of encouraging an alumnus to donate to the school in which they graduated. We try to control for the latter by choosing a set of donors who all graduated with a degree from the same school. Before we ran the study, we wanted to confirm whether our stratified random samples were not significantly different from each other. To do this, we provide some descriptive statistics for each of the four groups (See Table 2.4).

To see whether the groups are similar, we compare the differences in means of multiple variables for Groups 1 and 3 (started with no *Donation Variety*) and Groups 2 and 4 (started with positive *Donation Variety*). We find that there is no statistically significant difference between Groups 1 and 3 or Groups 2 and 4 on four dimensions: (1) average FY 2012 gift size, (2) average total past giving, (3) average number of years since their first gift, and (4) average time since graduation. We find there is no significant difference between the samples that included the business school and the others. This suggests donors who chose to give to single or multiple initiatives, whether it included (or did not include) the business school in the past, are not different in their donation behaviors over time.

For the field study, we treated each of the 200 donors from the two groups (1 and 2) who had given to the business school in the past as one set of controls by only targeting them with appeal letters which asked them to consider giving again to the same initiatives they had supported in the past, including the business school (i.e. the usual appeal all alumni from the focal university receive). We then randomly split the two groups (3 and 4) who had not yet given to the business school in the past into two groups of 200 each for each group. One half of each group (n = 200) received the control message asking them to consider giving again to the same initiatives they had supported in the past (not including the business school). Again, this is the usual appeal that each donor who gives the previous FY receives. The other half of each group received the treatment message asking them to consider giving to the same initiatives they had considered in the past and to *also* consider giving to the school where they had received their degree (i.e. the business school) as well. Thus, the only difference between the control and treated message was the addition of language which asked the donor to consider giving some money to the business school as well as the other initiative(s) that donor had supported in the past.

The study was run during the second half of FY 2013 (six months from January 1 to June 30, 2013). Initial emails and direct mails were sent to participants in January, and each donor received one email and one direct mail. A follow-up email and direct mail was sent in the beginning of May as a reminder to those donors who had yet to give in FY 2013. Donations were collected and recorded until the end of the FY 2013.

Results

To determine whether the field study was successful, we first want to determine whether donors who have already given to the business school in the past are similar in their giving patterns to donors who have yet to give to the business school. To do this, we compare the results for the control Groups 1 and 3 (no *Donation Variety*) and for the treated Groups 2 and 4 (positive *Donation Variety*). For Groups 1 and 3, we see that, out of the 200 donors contacted for each group with the control message, 86 and 88 donors respectively, responded positively with a donation (See Table 2.5 for detailed results). Further, we see that the average gift amount for Group 1 was $398 and for Group 3 was $381, which is not statistically significantly different ($t = 0.65$; $p = 0.51$). For Groups 2 and 4, we see that, out of the 200 donors contacted for each group with the control message, 140 and 141 donors respectively, responded positively with a donation. We also see that the average gift amount for Group 2 was $642 and for Group 4 was $625, which is not statistically significantly different ($t = 0.35$; $p = 0.73$). This suggests that any difference between the treatment and control groups for Groups 3 and 4 should be as a result of the change in marketing content and not from a donor's different giving histories.

Next, we want to see whether encouraging donors to increase their *Donation Variety* by asking them to consider adding the business school as another recipient of their donation was successful. To do this, we want to compare the results with Group 3 and Group 4 across the treatment and control groups. We see for Group 3 (no previous *Donation Variety*) that asking the donor to consider the business school as an initiative to support led to an increase from 88 to 119 gifts, a 35% increase in repeat giving, and an increase in the average gift size from $381 to $489, a 28% increase in donation size ($t = 4.57$; $p < 0.01$). Further, we saw an increase in *Donation Variety* from 0 to 0.395. We see for Group 4 (had positive *Donation Variety*) that asking the donor to consider the business school as an initiative to support led to an increase from 141 to 144 gifts, a 2% increase in repeat giving, and an increase in the average gift size from $625 to $835, a 33% increase in donation size ($t = 4.13$; $p < 0.01$). Further, we saw an increase in *Donation Variety* from 0.573 to 0.661.

Discussion

The results of this field study suggest that encouraging donors to support additional initiatives (especially when the additional initiative has a high degree of fit) can successfully increase both the number of donors who repeat and the donation amount. In the case of donors who have never spread gifts across multiple initiatives before (Group 3), we see that there was a significant increase in ***both*** the percentage of donors who were retained from the previous year and the average value of each donor's total gift. However, in the case of donors who have already spread gifts across multiple initiatives before (Group 4), we see that there was only a significant increase in the average value of each donor's total gift. This suggests that, when donors have only given to one initiative, successfully aligning the donor with an initiative which has a high degree of fit (in this case being an alumnus of the focal school) can impact both the total size of the gift and the decision of the donor to give in the first place. When donors are already spreading donations across multiple initiatives, encouraging donors to give to another initiative with a high degree of fit does not seem to affect the decision of the donor to make a gift to the university. However, it does seem to significantly increase the total amount of the gift.

Implications to Marketing Theory and Practice

Theoretical Implications

This study empirically tests the effect of the distribution of gifts across multiple initiatives of a non-profit, i.e., *Donation Variety*, on a donor's future value to the nonprofit and identifies factors that increase *Donation Variety*. The results of this study have several implications to marketing theory. First, we find that the amount and distribution of gifts across multiple donation options (measure of *Donation Variety*) is a good predictor of future donation behavior. We show that donors with a higher level of *Donation Variety* of their past gifts are more likely to give in the future and, conditional on the gift being made, are likely to give more than donors with a lower degree of *Donation Variety*. This offers some empirical validation to the literature on social impact theory and donor-nonprofit relationship management. In other words, donors who are more broadly tied to the nonprofit organization through multiple connections with various causes are more likely to stay engaged through subsequent gifts versus donors who may have given the same amount over time, but are more narrowly tied with fewer or even just one initiative. Further, we found empirical evidence that *Donation Variety* can also change a donor's responsiveness to the changes in macroeconomic environment. We find that donors with a higher degree of *Donation Variety* are less responsive to negative changes in the macroeconomic condition, making them less risky, as their donation patterns have lower volatility with external shocks. Besides, we tested the interaction effect between marketing efforts and *Donation Variety*. We found that donors with a higher *Donation Variety* are more responsive to marketing efforts of the foundation. More testing is necessary to validate this conclusion, as it might be the case that donors who end up giving to multiple initiatives might be more responsive to marketing efforts even before they begin giving to multiple initiatives. However, this result does offer some evidence that nonprofits can increase their return on marketing investments (ROMI) by focusing their marketing efforts on donors with a higher level of *Donation Variety*.

Second, we find that our measure of *Donation Variety* is better able to capture the variation in donation amount and better predict the expected donation amount (both in-sample and out-of-sample) than a measure of the number of initiatives supported and total of gift amount. This contributes to the literature on measurements of the depth and breadth of customer relationships. Further, it suggests that measures such as crossbuy (i.e. number of product categories purchase) commonly used in the CRM literature to measure the breadth of a relationship, could be enhanced by simultaneously capturing the depth of the relationship in each category purchased as a single measure (i.e. *Purchase Variety*).

Third, this study empirically shows that factors that drive *Donation Variety* systematically change over the course of the relationship between the donor and a nonprofit organization. We find that at the acquisition stage, donor intrinsic motivations (marketing efforts) are more (less) effective at driving donors to give to multiple initiatives at the acquisition stage rather than the retention stage. This is an important contribution to the literature on donation behavior, as studies to this point have not distinguished the changes in a donor's responsiveness to marketing efforts over the course of the donor-nonprofit organization relationship. In all, these findings suggest that measuring and understanding the distribution of gifts across multiple donation options is important when trying to understand a donor's motivation to make initial and subsequent gifts to nonprofit organizations.

Managerial Implications

This study also has several important implications to marketing practice. First, we provide a way for managers of nonprofit organizations to measure and manage the depth and breadth of gifts with a single measure we call *Donation Variety*. From an acquisition perspective, our study indicates that nonprofits should focus on trying to align donors with causes that are ‘close to the heart’ – whether it is one specific cause or many causes. However, from a retention perspective, our study indicates that nonprofit organizations can focus on expanding the relationship with donors by encouraging donors to give to additional causes rather than only continuing to support the same cause year after year. For many nonprofit organizations that silo their initiatives into separate sub-foundation departments (e.g. usually each school at a university has its own foundation which tries to maximize giving to that school), this suggests that the overall goal should be to try and share donors with other departments rather than get donors to only give to a single initiative. Encouraging donors to donate across multiple departments leads to an increase in the likelihood and amount of money a donor will provide the university on the whole in the future, and a buffer against the potential loss of donations due to an economic downturn. We even found some evidence that *Donation Variety* increases the responsiveness of donors to marketing efforts by the foundation, although further research is needed to provide stronger empirical evidence of the validity of this finding.

Additionally, our study provides causal evidence of the value of *Donation Variety* through a field study applied in marketing practice. We showed that, by altering the content of the marketing message with an appropriate appeal to increase *Donation Variety*, we were able to increase the likelihood and amount of giving by donors who had only to that point given to single initiatives and increase the amount of giving by donors who already had donated to multiple initiatives. This is important, as it offers external validation to academic research, making it more likely that other marketing research studies will be implemented in practice.

Limitations and Further Research

We do acknowledge that this study was completed with a single nonprofit organization. While this potentially limits the generalizability of the study, it requires significant effort to run a field study with a single firm (in this case an educational foundation), which is a significant contribution of this study. Further, while gifts to foundations make up a significant amount of the total giving to nonprofit organizations, future research in the nonprofit context can address this issue by continuing to test how depth and breadth of supporting multiple causes and fundraising projects offered by a nonprofit might affect a donor's total value to the nonprofit across different types of nonprofit organizations. Additionally, the findings from the study, with regard to measuring both depth and breadth of giving as a single measure, suggest that future research test whether a similar measure of purchase variety better captures cross-buying behavior.

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Table 2.1 Variable operationalizations and descriptive statistics

Variable	Mean	Standard Deviation	Operationalization
Single vs. Multiple Giving Behavior			
Multiple Giving	4.40%	N/A	% of the sample who gave to multiple initiatives in their first gift
	67.60%	N/A	% of the sample who have given to multiple initiatives by the end of FY 2012
Time until Multiple Giving	4.65	3.71	For a donor who starts off by giving to single initiative (95.6%), the average time (in years) from first donation until the donor starts to giving to a second initiative
Donation Variety	0.42	0.40	The average donation variety of a given donor at the end of observation period (FY 2012) as measured by Equation 1
Intrinsic Motivators			
Spouse at the University	32.10%	N/A	% of donors with a spouse who also went to the same university
Number of Degrees	1.20	0.50	Average # of degrees a donor received from the University
Extrinsic Motivators[*]			
Personal Marketing (#)	0.09	0.35	Average # of times each donor was invited to fundraising events and received personal visits from the university foundation each year
Impersonal Marketing (#)	0.49	0.36	Average # of mails and phone calls each donor received each year
Control Variables			
Gender	59.30%	N/A	% of female donors
In-state Resident	60.80%	N/A	% of donors residing in the same state as the focal university
Time Since Graduation	17.65	4.44	Average number of years since graduation at the end of observation period (FY 2012)
Average AGI	$73,076	$48,243	Average adjusted gross income (AGI) at the zip code level
Average Charitable Contribution	3.20%	2.60%	Average % of the AGI donated at the zip code level
Exchange Variables			
Average Donation Amount ($)	$381	$4,132	Average amount of donation per donor per year ($)
Total Donation Amount ($)	$2,391	$17,822	Average total amount of donation ($) made by each donor over the observation period
Total Number of Gifts	11.2	17.2	Average total # of gifts made by each donor over the observation period

[*] We use actual Personal and Impersonal Marketing Costs in the model rather than just the number of touches. However, we cannot provide the descriptive statistics (mean and standard deviation) of marketing costs at the request of the university foundation. We can note that the cost of each personal marketing touch is significantly larger (> 10x) than that of each impersonal marketing touch

TABLE 2.2: Results for the drivers and consequences models

Variables	DV = $Variety_{it}$		DV = $ln(Gift_{it})$	
	Selection Coeff. (Std. Err.)	**Main Coeff. (Std. Err.)**	**Selection Coeff. (Std. Err.)**	**Main Coeff. (Std. Err.)**
Intercept	-2.223 (0.027)*	0.177 (0.005)*	-0.032 (0.025)$^{n/s}$	2.412 (0.046)*
$ln(Gift_{i,t-1})$	0.102 (0.003)*	0.012 (0.0004)*	0.204 (0.003)*	0.252 (0.005)*
$Variety_{i,t-1}$	2.870 (0.021)*	0.802 (0.003)*	0.071 (0.021)*	0.157 (0.032)*
$First_{it}$	0.159 (0.078)**	0.150 (0.037)*	---	---
Extrinsic				
$ImpMktgCost_{it}$	0.012 (0.003)*	0.011 (0.001)*	0.044 (0.009)*	0.130 (0.020)*
$PerMktgCost_{it}$	0.096 (0.005)*	0.002 (0.0002)*	0.006 (0.002)*	0.032 (0.007)*
$Econ_{t}$	6.793 (0.397)*	0.118 (0.054)**	1.524 (0.377)*	4.753 (0.503)*
Intrinsic				
$Degrees_{it}$	0.092 (0.013)*	0.010 (0.002)*	0.065 (0.013)*	0.087 (0.025)*
$Spouse_{i}$	0.256 (0.013)*	0.008 (0.002)*	0.093 (0.014)*	0.005 (0.027)$^{n/s}$
Interaction Effects				
$Variety_{i,t-1}$*$ImpMktgCost_{it}$	---	---	0.043 (0.004)*	0.003 (0.001)*
$Variety_{i,t-1}$*$PerMktgCost_{it}$	---	---	0.001 (0.0004)**	0.002 (0.0005)*
$Variety_{i,t-1}$*$Econ_{t}$	---	---	-4.143 (0.774)*	-0.606 (0.101)*
$First_{it}$*$ImpMktgCost_{it}$	-0.015 (0.003)*	-0.001 (0.0004)**	---	---
$First_{it}$*$PerMktgCost_{it}$	-0.002 (0.001)**	-0.003 (0.0008)*	---	---
$First_{it}$*$Degrees_{it}$	0.106 (0.053)**	0.006 (0.003)**	---	---
$First_{it}$*$Spouse_{i}$	0.065 (0.013)*	0.001 (0.0002)*	---	---
Control Variables				
$Gender_{i}$	0.044 (0.012)*	0.016 (0.002)*	0.039 (0.013)*	0.439 (0.026)*
$Location_{i}$	0.036 (0.012)*	0.015 (0.002)*	0.054 (0.014)*	0.054 (0.025)**
Time Since $Graduation_{it}$	0.089 (0.022)*	0.002 (0.0003)*	-0.071 (0.002)*	0.033 (0.003)*
$AvgAGI_{it}$	0.001 (0.0001)*	0.0003 (0.0002)$^{n/s}$	0.0002 (0.0001)**	0.003 (0.0003)*
$AvgGiving_{it}$	0.655 (0.228)*	0.039 (0.038)$^{n/s}$	0.064 (0.024)*	0.643 (0.259)**
Control Function Variables				
$ImpMktgError_{i,t}$	-0.012 (0.012)$^{n/s}$	0.012 (0.001)*	-0.058 (0.009)*	-0.146 (0.020)*
$PerMktgError_{i,t}$	-0.093 (0.005)*	0.002 (0.0002)*	0.009 (0.002)*	-0.028 (0.007)*
Model Fit				
Log Pseudolikelihood	-13,723.53		-107,989.78	

* Significant at p-value < 0.01; ** Significant at p-value < 0.05; n/s Not significant at p-value < 0.05

TABLE 2.3: Donor selection using donation variety and cross-donation/total donation[a]

Percent of Donors Selected in FY2013	Donation Variety	Cross-Donation (Breadth) and Total Donation (Depth)
Top 10% of Donors	$94.9k	$88.9k
Top 15% of Donors	$104.2k	$98.1k
Top 25% of Donors	$115.9k	$110.0k

[a] Total values are all rescaled by the same constant at the request of the focal university foundation

TABLE 2.4: Descriptive statistics for field study

Group	**2012 Gift Size[a]**	**Total Past Giving[a]**	**Years Since First Gift[a]**	**Time Since Graduation[a]**
(1) No Variety – Only B-School	$447 ($270)	$2,208 ($5,743)	12.7 (6.7)	21.5 (15.2)
(2) Variety – Including B-School	$801 ($410)	$8,989 ($15,899)	13.4 (6.1)	25.0 (11.1)
(3) No Variety – No B-School	$455 ($255)	$2,402 ($6,192)	12.9 (6.3)	21.4 (15.4)
(4) Variety – No B-School	$790 ($428)	$8,690 ($15,024)	13.2 (5.9)	24.4 (11.4)

[a] Mean (Std. Dev.)

TABLE 2.5: Results from the field study

	Message Content	
Group	**Control**	**Treatment**
(1) No Variety – Only B-School	Made a Gift (%): 86 (43%) Avg. Gift (Std. Dev.): $398 ($261)	N/A
(2) Variety – Including B-School	Made a Gift (%): 140 (70%) Avg. Gift (Std. Dev.): $642 ($494)	N/A
(3) No Variety – No B-School	Made a Gift (%): 88 (44%) Avg. Gift (Std. Dev.): $381 ($260)	Made a Gift (%): 119 (59.5%) Avg. Gift (Std. Dev.): $489 ($210)
(4) Variety – No B-School	Made a Gift (%): 141 (70.5%) Avg. Gift (Std. Dev.): $625 ($487)	Made a Gift (%): 144 (72%) Avg. Gift (Std. Dev.): $835 ($530)

Figure 2.1: Model free evidence: before and after giving to multiple initiatives

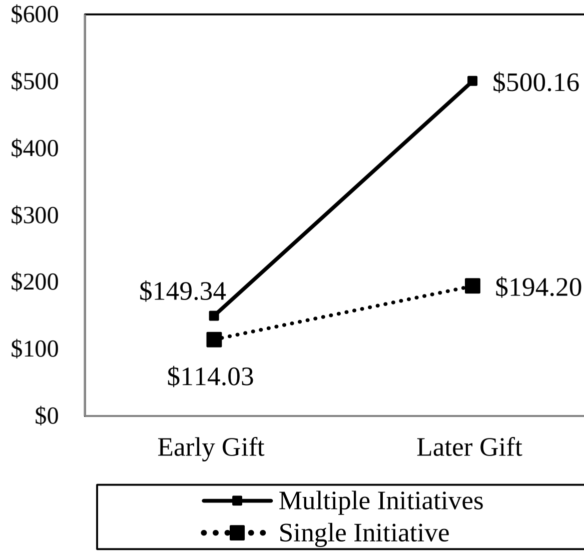


Figure 2.2a: Degrees and donor lifecycle

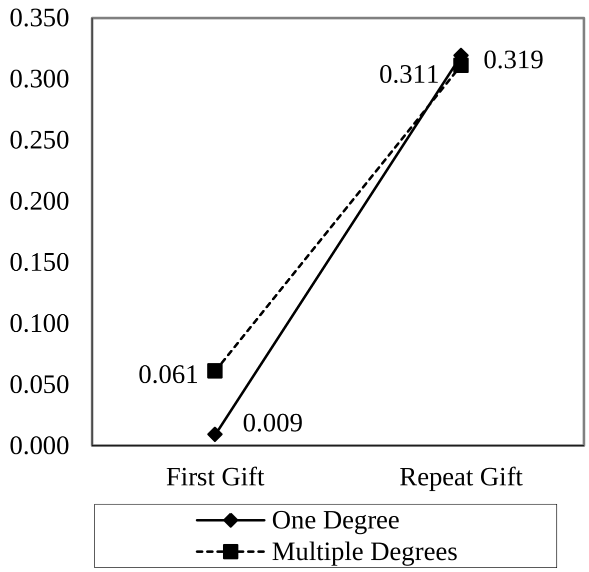


Figure 2.2b: Spouse and donor lifecycle

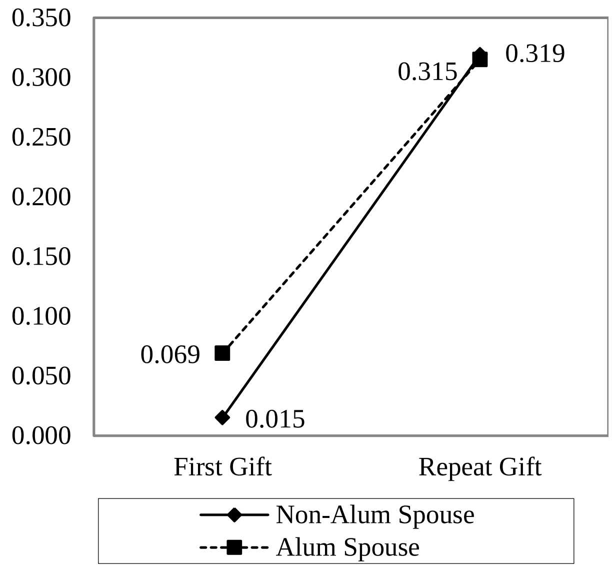


Figure 2.2c: Impersonal marketing and donor lifecycle

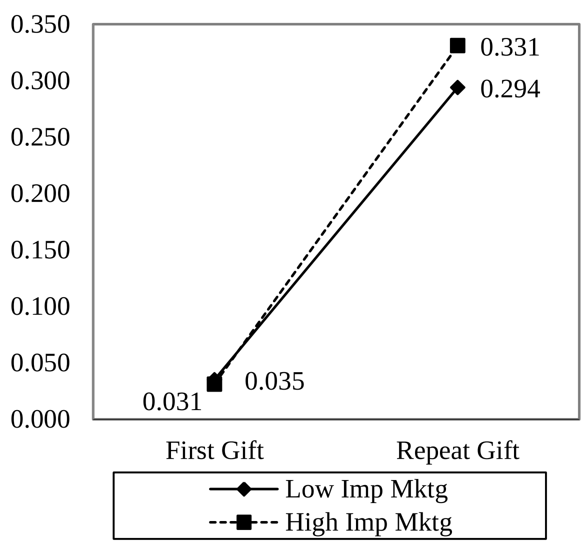


Figure 2.2d: Personal marketing and donor lifecycle

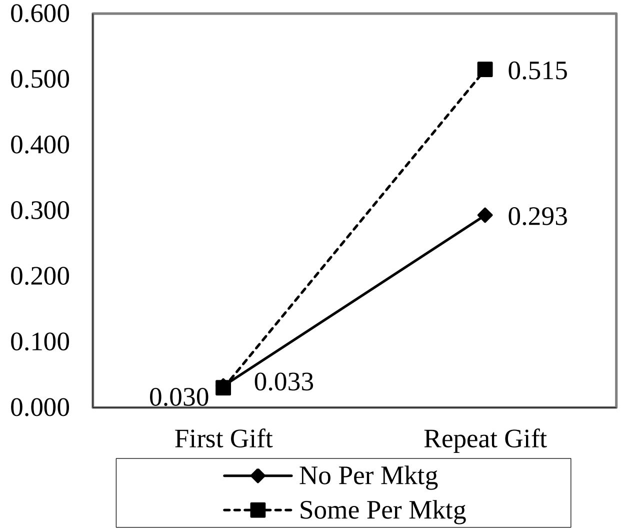


Figure 2.3a: Economic condition and donation variety

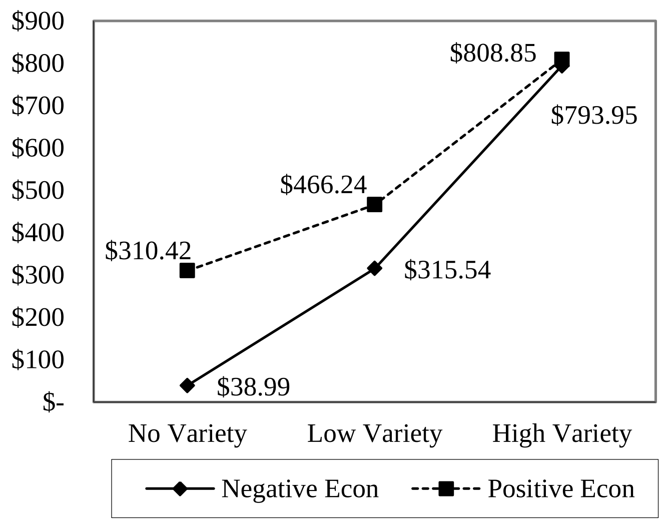


Figure 2.3b: Impersonal marketing and donation variety

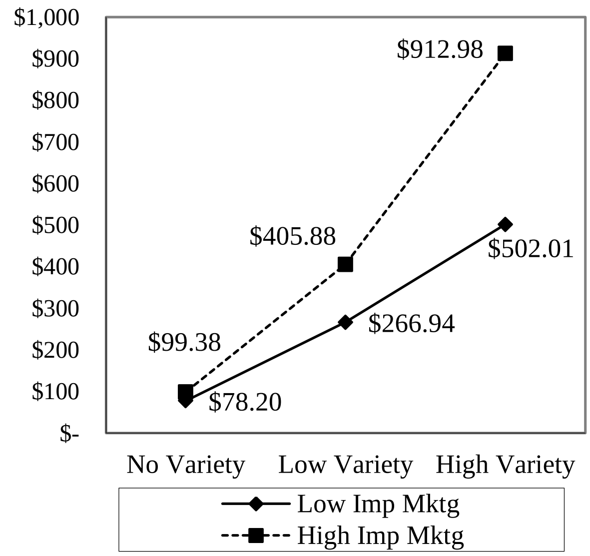
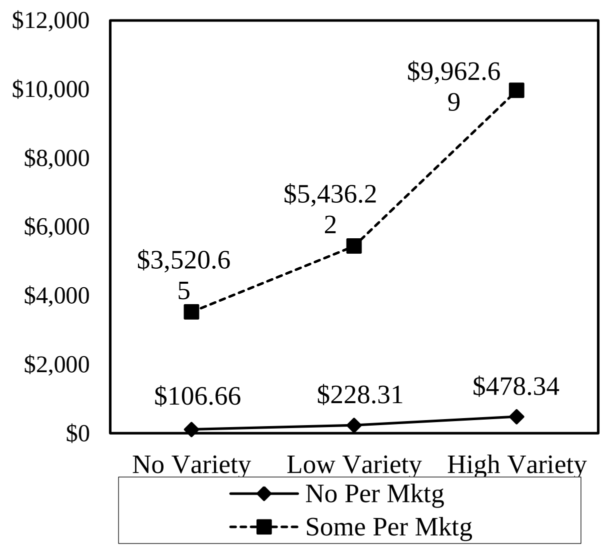


Figure 2.3c: Personal marketing and donation variety



CHAPTER 3: CUSTOMER LOYALTY PROGRAM USAGE ACROSS FIRMS

Abstract

Many firms across various industries offer loyalty programs, each with the goal of enhancing customer retention at their respective firms. However, it is common that customers are members of and influenced by loyalty programs across many different firms. This research investigates how a customer's loyalty program usage, in this case reward redemption, with a focal firm's loyalty program impacts that customer's search and transaction behavior at the focal firm as well as with competing firms. To do this, we use a novel dataset from a mobile advertising and loyalty app provider which partners with multiple firms and allows customers to manage relationships with independent loyalty programs across those different firms. The dataset includes a random sample of 2051 customers from the mobile app that have interacted with six local restaurants over a 90-week period. Our analysis reveals that over time customers buy less frequently at each store while purchasing across more stores. However, redeeming a reward at one store can keep the customer more loyal to that store. We match customers based on their probability of redeeming a reward at the focal store and we find that within a short period post-redemption (8 weeks), customers who redeem a reward will visit the store more often and spend more on average, as compared to those customers who have accumulated the same amount of points, but did not redeem any reward. Interestingly, we see that during this period customers who redeemed a reward will also become more interested in competitive offerings, and will visit other stores more often and spend more across these stores as compared to non-redeemers. These findings suggest that redeeming a reward has positive effect on customer behavior at the focal

store, but also makes them more prone to look for other offers once they utilize the points they have accumulated at that store. Furthermore, our analysis of redeemers' post-redemption behavior reveals that redeeming a reward has much more positive effect on light users as compared to heavy users. This suggests that firms should not focus their reward programs only on their most frequent customers, and should also reward their less engaged customers as a means to increase their loyalty to the firm.

Keywords: Loyalty programs, Reward redemptions, Point pressure, Rewarded behavior

Introduction

Most firms have adopted loyalty programs to enhance customer profitability by offering customers rewards for repeat purchases. However, most customers are not 100% loyal to one firm. Instead, customers are often members of loyalty programs at competing firms and make purchases across those competing firms over time. This behavior is referred to as "polygamous loyalty" (Dowling and Uncles 1997). One of the key reasons customers might make purchases across firms with different loyalty programs is to maximize the benefits they receive from those competing loyalty programs[11]. For instance, in a recent survey of airline loyalty members, 84% of shoppers say airline loyalty programs influence them to engage with a particular brand[12]. Yet, only 10% of fliers are loyal to an airline, and half of those would switch if given $50 off another

[11] 2015 Loyalty Report, Bond Brand Loyalty, available from: http://info.bondbrandloyalty.com/the-loyalty-report-2015

[12] 2014 Shopper Experience Study, available from: http://www.cognizant.com/shopper-experience-study

airline[13]. This provides some evidence that a customer's behavior with a given firm can be simultaneously dependent on the focal and competing firm's loyalty program benefits.

Thus, in order to investigate how a loyalty program affects a customer's behavior in a competitive market, one needs to consider a customer's interactions across all firms and loyalty programs (Leenheer et al. 2007; Liu and Yang 2009). However due to data limitations, research in the customer relationship management (CRM) literature, specifically with regard to loyalty programs, is often studied within the frame of a single firm (e.g. Bolton, Kannan, and Bramlett 2000; Kivetz and Simonson 2002; Lal and Bell 2003; Lewis 2004; Liu 2007; Kopalle et al. 2012; Taylor and Neslin 2005). There has yet to be much research that sheds light on how customers interact across firms with competing loyalty programs. The goal of our research is to cover this gap by exploring customer loyalty program usage across competing firms. More specifically, our study answers the following key research question:

How does loyalty program usage at a given firm impact a customer's future behavior at the focal firm and future behavior with competing firms?

Here we define customer behavior as both a customer's search and purchase behavior at a given firm, where search behavior includes search for rewards and purchase behavior includes both the frequency of purchase and the average amount of purchase. To answer our key research question we investigate how loyalty program usage, in this case reward redemption, at one firm affects customer search and purchase behavior at both the focal and competing firms.

Our research contributes to a better understanding of the impact of loyalty programs on customer behavior in two ways. First, we investigate the effect of loyalty program usage on customer behavior at the focal firm, controlling for that customer's interaction across competing

[13] Fly.com Survey; available from: www.fly.com/release/3185/download

firms. In many product categories, customers make purchases across multiple firms and may be a member of multiple loyalty programs that these firms offer to their customers. By purchasing across multiple firms over time, a customer accumulates loyalty points at more than one firm. Once a customer redeems some (or all) of the points she has accumulated at one firm to receive a reward, that customer faces a decision to either: (1) accumulate more points for future redemption opportunities at the focal firm by continuing to purchase at that firm, or (2) increase purchases at one or some other firms in order to receive benefits from a competitor's loyalty program as well. Therefore, getting a reward from a loyalty program may impact a customer's future transactions with that firm, specifically if the customer is simultaneously a member of other multiple loyalty programs. By controlling for customers' purchases across competing firms, we can isolate how redeeming a reward at one firm impacts a customer's future relationship with that firm.

Second, we investigate how a customer's loyalty program usage at the focal firm potentially spills over onto that customer's search and purchase behavior across competing firms. The majority of research on loyalty programs study the impact of loyalty program on customer behavior within a single firm and do not consider the cross-firm effects of loyalty programs on customer behavior (Leenheer et al. 2007; Liu 2007; Liu and Yang 2009; Verhoef 2003). Of the few studies that consider multiple loyalty programs most, focus on program membership and investigate whether membership in multiple loyalty programs affects customer share of wallet across firms (e.g. Mägi 2003; Meyer-Waarden 2007; Leenheer et al. 2007; Liu and Yang 2009; Kopalle and Neslin 2001; Zhang and Breugelmans 2012). Unlike these studies, we investigate how actual usage of a loyalty program (i.e. redemption of a reward) at one firm affects customer behavior across firms. We believe that studying customers' active usages of loyalty programs can generate insights about how loyalty programs affect customer behavior in a competitive market (Dorotic et al. 2011 and 2014; Taylor and Neslin 2005).

Third, we focus on those customers who redeemed a reward and investigate the differences in their pre- and post-redemption behavior. We would like to know whether getting a reward from a firm may induce different responses from different types of customers, specifically more versus less frequent customers. A general perception among managers is that loyal customers who purchase more frequently from a firm are the best target for loyalty programs. A firm can use a loyalty program to reward its best customers and increase the sale to these loyal customers (Reinartz and Kumar 2002; Wansink 2003). However, some recent studies have shown that loyalty programs generate more positive outcomes for less frequent customers than for loyal customers (Lal and Bell 2003; Liu 2007). Therefore, we would like to test whether reward redemption causes different responses from loyal and casual customers.

We answer our key research questions by analyzing customer behavior across six loyalty programs of competitive local vendors in a city in the mid-Atlantic region of the United States that encompasses a major public university. Our empirical analysis shows that a customer's search and purchase behavior evolves within a loyalty program at a firm over time *and* that a customer's usage of the loyalty program at one firm impacts that customer's search and purchase behaviors at the focal firm and across competing firms. At the focal firm, redeeming a reward has positive effect on a customer's future search and purchase behavior at that firm. This provides support to the CRM literature which suggests that rewards from loyalty programs usually increase future customer retention and purchase behavior.

Further, we also find that there is a spillover effect of loyalty program usage at one firm on the customer's behavior at competing firms. Customers who redeemed a reward at one firm search more for rewards across other firms as compared to customers who have not yet redeemed a reward at the focal firm. Once customers redeem a reward at the focal firm, they also broaden their purchase consideration set and start to transact more frequently with other firms suggesting that reward redemption can in some cases cause the customer to explore new options at competing firms. This key finding suggests that firms should be careful in designing loyalty programs which take into account not only the positive impact of customer behavior at the focal firm, but also the potential that reward redemptions at the focal firm may influence customers to search and transact more with competing firms.

Finally, we run an exploratory analysis of post-redemption behavior for customers who redeemed a reward at one of the focal firms. We find that heavy users decrease their spending after redeeming a reward, while light users continue to purchase at same rate after redemption. These findings suggest that firms should not focus their reward programs only on their most frequent customers, and should also reward their less engaged customers as a means to maintain their loyalty to the firm.

Overall, our analysis highlights the importance of both between-group comparisons of the behavior of redeemers and non-redeemers as well as within-group comparison of redeemers. If we only consider the post-redemption behavior of redeemers, it seems that redemption has a negative effect on customer behavior for heavy users, and no significant effect on behavior of light users. However, compared to non-redeemers, those who redeem a reward do stay more loyal to the focal firm on average. This is an important observation, specifically for product categories in which consumers' variety seeking is relatively high, and it might help to explain the mixed support found by studies on the effectiveness of loyalty programs (e.g. Leenheer et al. 2007; Magi 2003; Shugan 2005).

Theory Development

Customers go through a series of stages in their buying process. Before making a decision to purchase, a customer seeks information about available alternatives. This information can come from prior experiences with a product or firm or by searching for new information. Based on personal experiences and additional information gathered through search, the customer can then evaluate the utility of making a purchase at a given firm. As long as the utility of purchasing is positive for at least one of the alternatives, the customer will choose to purchase the alternative with the highest utility.

One factor that can positively influence the utility of purchasing is the presence of a reward program. If a firm offers a reward program, the customer will accumulate points based on all of the past and current purchases. Those points can be redeemed to obtain rewards, e.g. free or discounted products, upgrades, and/or additional services. These rewards can have instant effect on purchase utility (e.g. discount and coupons), or may have a long term effect (i.e. customer accumulates points to obtain a reward in future). Therefore, loyalty reward programs can influence a customer's choice of a firm over time. A customer may prefer a firm who offers more rewards for one dollar worth of purchase as compared to competitors, or that customer may be willing to pay a higher price for a product to accumulate more points. Once a customer has accumulated enough points from a firm, that customer can make a decision on whether to redeem points for a reward at that firm on a subsequent purchase occasion. If the customer chooses to use points in order to redeem a reward for a given purchase, then the customer can evaluate whether to purchase again at the same firm or whether it is worthwhile to explore other purchase options at other firms in the future.

We expect that redeeming a reward impacts a customer's purchase behavior through two behavioral mechanisms: the point pressure mechanism and the rewarded behavior mechanism. Before redemption, the point pressure effect motivates customers to increase their purchase rates and amounts in order to reach the threshold to obtain a reward (Kopalle et al. 2012; Lewis 2004; Taylor and Neslin 2005). Then once a customer redeems a reward, two things happen. First, the point pressure decreases as the customer is no longer as close to obtaining a reward, and second, the rewarded behavior mechanism motivates the customer to make future transactions with the focal firm (Dreze and Nunes 2011; Taylor and Neslin 2005). We provide more details on these two mechanisms below.

Point Pressure Mechanism

The point pressure mechanism suggests that as a customer gets closer to obtaining a reward, that customer often increases purchase rates and amounts until she obtains enough points to qualify for a reward. This process of accelerating purchase behavior as a customer gets close to having enough points to redeem a reward has two main drivers: switching costs and forward-looking orientation (Taylor and Neslin 2005). Customers tend to perceive a higher switching cost due to the increasing anticipation of obtaining a reward. For example, Taylor and Neslin (2005) study a grocery store's reward program and found that point pressure has a significant effect on customers who are more inclined to immediate price discounts. In addition, the point pressure effect becomes even stronger as a customer progresses toward obtaining a reward (Hartmann and Viard 2008; Kivetz, Urminsky, and Zheng 2006). On the other hand, a forward-looking customer takes into account the utility of future periods into her current purchase decision, suggesting that the opportunity cost of forgoing points at the focal firm can be relatively high and influence a customer to continue to purchase until that customer can redeem points for a reward (Lewis

2004). For example, in an experimental study, Nunes and Derez (2006) manipulate the level of progress toward a goal. Their study shows that the likelihood of completing the task is higher when a task is perceived to be undertaken partially as compared to a task that has not yet begun. This suggests that forward-looking customers are more likely to account for the total value of their points already accumulated in future transaction opportunities. And, the closer the customer is to a reward, the more the customer will value obtaining reward points from the focal firm.

Several studies report the existence of the point pressure effect in different reward programs including a hotel's reward program (Kopalle et al. 2012), a grocery store's reward program (Lal and Bell 2003; Taylor and Neslin 2005), and coalition loyalty program of multiple retailers across industries (Dorotic et al. 2014). Specifically, Dorotic and colleagues (2014) show that customer purchase increases prior to redemption even in a reward program with no point expiration in which customers can redeem a reward at any time.

Based on this empirical evidence, the point pressure mechanism is likely to have a significant impact on increasing customer purchase behavior at the focal firm immediately before the customer has accumulated enough points for a reward redemption. However, once a customer redeems some (or all) of her points at one firm, the point pressure at that firm is likely to decrease. This will lower the value the customer places on the reward program at the focal firm when that customer is making a future purchase decision. Further, it also suggests that there is a higher likelihood that a customer will find a competing alternative more attractive as reward points at the focal firm no longer play as significant a role in driving the utility of a future purchase.

Rewarded Behavior Mechanism

Rewarded behavior is the long-term impact of a loyalty program on a customer's ongoing purchase behavior. Without the rewarded behavior effect, rewards can act like a promotion only increasing short-term sales, but can have little, no, or even a negative impact (i.e. stockpiling) after the promotion ends (Taylor and Neslin 2005). The two main drivers of the rewarded behavior mechanism are behavioral learning and cognitive affect. Based on behavioral learning theory, when a customer is rewarded for her purchases, the customer is more likely to repeat purchase (Rothschild and Gaidis 1981; Taylor and Neslin 2005). This happens as the customer learns to associate rewards with purchases from a given firm. And over time, the customer begins to value purchases from that firm even more regardless of the amount of reward points the customer currently has in her loyalty program account. From a cognitive affect perspective, receiving a reward prompts feelings of gratitude and appreciation toward the firm. This positive feeling enhances the customer's attitudinal loyalty and increases the likelihood that the customer will purchase again from the same firm (Dorotic et al. 2014; Lewis 2004; Drèze and Nunes 2011; Taylor and Neslin 2005).

Several studies have found evidence of the rewarded behavior mechanism. Taylor and Neslin's (2005) empirical study shows an increase in store sales over a 7-week period after the reward period ended. This is evidence that customers continued to value purchasing at the firm even when the value of the reward went away. Kopalle and colleagues (2012) study a hotel loyalty program, which has both components of frequency reward and customer tiers. Their analyses show that both components have a positive effect on rewarded behavior effect. However, customer tier can generate a stronger rewarded behavior effect, since the customer's utility of attaining a higher tier is not temporary. Their study also shows that there is customer heterogeneity in the response to reward programs. They find that the rewarded behavior effect is stronger among the price-sensitive segment. On the other hand, Dorotic and colleagues (2014) provide empirical support for the rewarded behavior effect across all customer groups (age, income, relationship duration). The authors study customer behavior in a coalition loyalty program of multiple retailers across industries. Their study shows that right after reward redemption that there will be an increase in purchase rate and purchase amount of all groups of customers. These empirical studies suggest that the rewarded behavior mechanism motivates a customer's future transactions with the focal firm after the customer redeems a reward at that firm, even if the customer is not close to receiving any rewards in the future.

Hypotheses Development

The goal of this study is to understand how a customer searches for information about as well as makes decisions to purchase from a focal firm and competing firms immediately after that customer redeems points from a loyalty program to receive a reward at the focal firm. We expect that the point pressure and reward behavior mechanisms will play a key role in driving that customer's ongoing search and purchase behavior after reward redemption. In this section we use the point pressure and rewarded behavior mechanisms to help develop several hypotheses relating to a customer's search for promotions as well as purchase behavior (frequency and amounts) immediately after a loyalty program reward redemption.

Information search is an important stage of buying process. In addition to relying on previous purchase experiences, customers commonly search for information across competitive alternatives as they approach their decision to purchase (De los Santos, Hortaçsu, and Wildenbeest 2012; Moe and Fader 2004; Moorthy, Ratchford, and Talukdar 1997; Punj and Moore 2009; Srinivasan and Ratchford 1991; Wiesel, Pauwels, and Arts 2011). Search for information not only impacts purchase decisions, but it may also impact reward redemption decisions. Customers who are more interested in obtaining rewards and deals are likely to gather more information about alternatives before making a purchase decision (DelVecchio 2005; Huang and Zhang 2011; Taylor and Neslin 2005). Consequently, we expect customers who search more for rewards offered by a firm are more likely to try to accumulate points so that they can redeem a reward at that firm in the future (Pancras, Venkatesan, and Li 2014). Further, we argue that once a customer redeems a reward at one firm, that customer's future search before the next purchase occasion would be affected by the past reward redemption decision.

Furthermore, redeeming a reward is likely to impact a customer's decision about future purchases (Dreze and Nunes 2011; Lewis 2004; Taylor and Neslin 2005). Once a customer uses the accumulated points (some or all) to redeem a reward at one firm, the customer may choose to repeat purchase at the focal firm to add points to the depleted point stock and to obtain additional rewards in future. On the other hand, in the absence of point pressure effect at focal firm, a customer may switch to another firm to accumulate points for potential rewards at that firm, or just to add more variety to the purchase (Kahn 1995; Zhang, Krishna, and Dhar 2000). We expect both the rewarded behavior and point pressure mechanisms impact the customer decision to repurchase from the local firm or switch to another firm.

Effect of Loyalty Program Usage on Customer Behavior at the Focal Firm

We expect that redeeming a reward at the focal firm is likely to have a positive effect on a customer's experience with that firm (Drèze and Nunes 2011; Roehm, Pullins, and Roehm 2002). The rewarded behavior mechanism suggests that once a customer redeems a reward at a firm, that customer becomes more interested in redemption opportunities to re-experience the joy of being rewarded at that firm. This suggests that the customer who receives a reward is likely to search for rewards offered by the focal firm more than a customer who has not yet experienced the rewarded behavior effect. Thus, we hypothesize:

H1a: Reward redemption at the focal firm has <u>positive</u> effect on future search for rewards offered by the focal firm.

The rewarded behavior mechanism suggests that redemption has positive impact on customer loyalty and the likelihood of repeat purchase at the focal firm. As discussed, multiple studies show that customers who have redeemed a reward at the focal firm have greater behavioral loyalty to that firm (Bolton, Kannan, and Bramlett 2000; Lal and Bell 2003; Roehm, Pullins, and Roehm 2002; Taylor and Neslin 2005). Further, it is reasonable to assume that customers have a budget constraint which can limit their spending level. However, we expect that a redemption of reward is perceived by the customer as a cost savings which allows the customers to spend some (or all) of that cost savings on future immediate purchases. Thus, we hypothesize that:

H1b: Reward redemption has a <u>positive</u> effect on the future purchase frequency at the focal firm.

H1c: Reward redemption has a <u>positive</u> effect on the future purchase amount at the focal firm.

<u>Effect of Loyalty Program Usage on Customer Behavior across Other Firms</u>

The point pressure mechanism suggests that before redemption, a customer is highly motivated to transact more with the focal firm to reach the threshold of rewards offered by that firm. However, the point pressure effect is likely to diminish once the customer redeems a reward at the firm. Depletion of point stock suppresses the urge to make all transactions at one firm in hope of obtaining a reward since the ability to obtain a reward is now much farther away into the future. This can give the customer a perceived opportunity to shop around and explore new options. Further, we expect that the rewarded behavior mechanism will make customers more interested in understanding how to obtain rewards available at competing firms now that they have recently experienced the value of redeeming a reward (even though it was not at the focal firm). As a result, we expect that customers who have redeemed a reward at one firm are likely to search more across competing firms than customers who have not yet used their accumulated points to get a reward from the focal firm. Thus, we hypothesize:

H2a: Reward redemption at the focal firm has a <u>*positive*</u> *effect on future search for rewards offered by competing firms.*

We argued that due to a decrease in point pressure, redeeming a reward at the focal firm has positive effect on a customer's search across other firms. This search for alternatives will broaden customers' consideration set and allow them to better evaluate options at other firms. This suggests that a customer would be more likely to examine new options and consider a competing firm for her next purchase occasion. Further, the customer is likely to perceive that the redemption of a reward from the focal firm is a cost savings (i.e. receiving something of monetary value for points). And, the customer is likely to see an opportunity to allocate a some (or all) of that cost savings to either purchase more at the focal firm or to try a new option at a competing firm without increasing the customer's total budget constraint. Thus, we expect that the reduction in point pressure is likely to increase the customer's desire to try alternative options from competitors. Therefore, we hypothesize:

H2b: Reward redemption at the focal firm has a <u>*positive*</u> *effect on the future purchase frequency across competing firms.*

H2c: Reward redemption at the focal firm has a <u>*positive*</u> *effect on the future purchase amount across competing firms.*

Empirical Application

We empirically test our hypotheses using a novel dataset from a mobile advertising and loyalty app provider which partners with firms and allows customers to manage relationships with independent loyalty programs across those different firms. The majority of retailers on this app are local restaurants, and we focus our empirical application in the restaurant industry. We believe it is an appropriate industry to test our hypotheses for the following reasons: (1) It is one of the fastest growing sectors in terms of loyalty program memberships, and (2) There are currently there are more than 54 million memberships in restaurants loyalty programs across the United States[14].

Data

We focus our empirical analysis on customers' searches and transactions with multiple local restaurants in a US city in the mid-Atlantic surrounded by a university campus. We draw a sample of customers who are members of the mobile app and have interacted with at least one of 6 local restaurants which were among the first vendors that joined the app. These restaurants are all located in close geographical proximity in the downtown area of the city and offer relatively similar menus and prices, i.e. they compete for the same set of customers in terms of location, price, and selection. Our dataset consists of each customer's search, transaction, and reward redemption behaviors with these six restaurants over a 90-week period from July 2011 to March 2013.

In order to test the effect of loyalty program usage (i.e. reward redemption) on customer search and transaction behavior, we need to obtain a sample of customers from the database

[14] COLLOQUY Loyalty Census 2015, available at: https://www.colloquy.com/reports

which have both redeemed and not redeemed rewards at each of the restaurants. This will allow us to compare the behavior of a customer who redeems a reward (treatment) controlling for the behavior of a customer who does not redeem a reward (control). We construct our sample as follows. First, we need to create a sample of all of the customers that have redeemed a reward at each restaurant (i.e. redeemers). In this case a customer is coded as redeemer if that customer redeemed a reward during the observation period. Next, we need to create a sample of customers that have not redeemed a reward at each restaurant. We note that there are two types of non-redeemers: (1) Those that have accumulated enough points and/or been transacting at the restaurant long enough to be likely to redeem a reward, and (2) those that have yet to accumulate enough points and/or not been a customer long enough that we would expect a redemption to occur. Our goal is to only sample from the customers who fit the first criteria and not the second. In order to do this, for redeemer group we calculate how long it takes from the first transaction with a firm until the customer redeems a reward at that firm. We use it as the expected redemption time for non-redeemers at each restaurant. Then, we drop any non-redeeming customer from each restaurant who either does not have the accumulated points required for a redemption or has not been transacting with the restaurants past the expected redemption time. The final sample includes 2051 customers, where 699 of these customers have redeemed at least one reward in one of the restaurants. During the observation period, the customers had 21,726 transactions, and searched for rewards 2,791 times. Detailed descriptive statistics about customer search and purchase can be found in Table 3.1 (See Table 3.1)

Model Free Evidence

We first run an exploratory analysis on our sample of redeemers and non-redeemers. We calculate the average customer behavior of redeemers before and after redemption periods. For non-redeemers, we use the expected time of redemption to split the time into before and after redemption periods and similarly calculate the average customer behavior during these two periods. Figure 3.1a and 1b show the average inter-purchase time of the two groups of customers before and after redemptions (See Figure 3.1a and 3.1b).

Figure 3.1a shows the average inter-purchase times at the focal firm. As we see, before redemption the average inter-purchase time of redeemers is shorter than non-redeemers. However the difference between the two groups is rather small (3.4 weeks). After the redemption[15] both groups slow down their purchase rate, but there is significant difference in purchase rates of redeemers and non-redeemers (20 weeks). After redeeming a reward, redeemers keep purchasing from the focal firm, albeit less frequently than they did before redeeming the reward. But, it seems that customers who have not redeemed any reward eventually stop visiting the focal firm and abandon the points they have accumulated at that firm. This provides some evidence that redeeming a reward leads to more positive customer behaviors, in this case a shorter average inter-purchase time at the focal firm relative to non-redeemers.

Figure 3.1b shows the average inter-purchase time of customers across competing firms before and after the redemption time period. Before the expected redemption time period at the focal firm, the non-redeemer group purchases more frequently at competing firms when compared to the redeemer group. In this case, the average inter-purchase time of non-redeemers is about 7 weeks shorter for the non-redeemer group. This is likely the case since the customers who are more likely to redeem at the focal firm are also more likely to purchase more frequently at the focal firm, i.e. less frequently at competing firms. However after the expected redemption time period, the average inter-purchase time for non-redeemers is 14 weeks longer as compared

[15] Expected redemption for non-redeemers based on average time to redemption of redeemers.

to the pre-redemption inter-purchase time. But for redeemers, the difference in inter-purchase time before and after redemption is only 1.7 weeks.

This model free evidence provides some support for the hypotheses related to post-redemption purchase behavior at both the focal and competing firms. However, this model free evidence does not control for several potential alternative explanations. For example, it does not control for differences across customer preferences for a given restaurant or for rewards in general. Thus, it is important to develop a model which can control for these alternative explanations and formally empirically test our hypotheses.

Methodology

Our study aims to evaluate the impact of reward redemption on customer search and purchase behavior. In order to do this, we need to control for how a redeemer would have behaved differently had she not redeemed a reward. However, this behavior is not observable since each customer can choose whether to redeem a reward or not. In a randomized experiment, one can use the average behavior of customers who have not redeemed a reward as an appropriate substitute for the average behavior of the redeemers in the absence of redemption (Rubin 1974). However, the redemption decision is likely not random. Customers who have redeemed a reward might be more interested in the focal firm than non-redeemers. As a result, the behavior of the two groups of customers would be different even in the absence of the reward redemption. Therefore, we first need to address the self-selection bias of the redemption decision.

There are two approaches to address this self-selection bias. One approach is to use instrumental variables. To do this we would need to identify variables that affect the redemption decision, but are unrelated to ongoing customer search and purchase behavior. We believe that identifying variables like these poses a significant challenge. Thus, finding a good instrument may not always be practical (Bound, Jeager, and Baker 1995; Hall, Rudebusch, and Wilcox 1996). The second approach is to create a matched sample of non-redeemers who are similar to redeemers immediately before the redeemers choose to redeem a reward. In this approach one need to match customers in the two groups so that before redemption, there are no systematic differences between redeemers and non-redeemers. This is the same as randomizing group assignment in a natural experiment (Rosenbaum and Rubin 1983; Rubin 1974; Rubin and Thomas 1996).

Propensity score matching allows us to match redeemers and non-redeemers with similar characteristics (Rosenbaum and Rubin 1983, 1985). In this case, the propensity score is the probability of a customer redeeming a reward. Using this score we match each redeemer with a non-redeemer who has the closest propensity score to that redeemer. Matching based on propensity scores will create a sample of redeemers and non-redeemers for whom their characteristics have similar distributions at the baseline (i.e. right before redemption).

Redemption decision. To build the sample, we first model the decision to redeem points for a reward. To do this we select a set of variables which are likely to influence a customer's decision to redeem a reward at the focal firm: (1) the points a customer has obtained at the focal and competing firms, (2) the length of time a customer has been with the focal firm, and (3) the number of rewards that were available at each firm at the redemption time and how far a customer is from the minimum rewards. We estimate the probability of redemption with a logistic regression as follows:

$$\begin{aligned} \text{Redeem}_{ij} = {} & \beta_0 + \beta_1 \text{Point}_{ij} + \beta_2 \text{Point\_Other}_{ij} + \beta_3 \text{Tenure}_{ij} + \beta_4 \sum_k \text{Rewards}_k \\ & + \beta_5 \text{Dist\_Min\_Reward}_{ij} + \varepsilon_{ij} \end{aligned} \tag{1}$$

where Redeem is a binary variable which equals 1 for customers who redeemed a reward and 0 for customers who did not redeem a reward at a given restaurant, Point is the point stock of customer i at the focal firm j at the time of redemption, Point_Other is the customer's average point stock at other firms at the time of redemption, Tenure is the time (in weeks) since a customer has joined the app, $Reward_k$ is the total number of rewards that are available at firm k at the time of redemption (k=1,..5), $Dist\_Min\_Reward_{ij}$ captures the distance between customer i's point stock at the firm with min reward available at the store at the time of redemption (the variable equal 0 if the customer has sufficient number of points to redeem the smallest available reward offered by that particular firm), and ε is the error term which is distributed extreme value.

Propensity Score Matching. Once we obtained propensity scores from estimating Equation 1, we match each redeemer with a non-redeemer in the sample who has the closest propensity score to that redeemer. Our matching approach is nearest neighbor, one-to-one matching with no replacement (Caliendo and Kopeinig 2008). We also used caliper for the matching to limit the tolerance for the difference in propensity scores of redeemers with their closest match. Matching with caliper may reduce the sample size if there is no good match for a redeemer within the tolerance zone. However, it will also reduce the bias in matching (Austin 2011; Caliendo and Kopeinig 2008).

After matching, we evaluate the quality of matching as follows. First, we run two-sample t-tests on the mean value of the covariates in the redemption model (Eq. 1), to compare the mean values for redeemers and non-redeemers (Rosenbaum and Rubin 1985). Before matching, significant differences in mean values for the two groups is expected. However, after matching we expect no systematic difference in the mean values of covariates between the redeemer and non-redeemer groups. This will assure us that redeemer and non-redeemer customers in the matched sample are not significantly different with regard to the factors that affect a customer's probability of redeeming a reward.

Second, we test that to what extent we were able to reduce the bias in the mean values of these variables between redeemers and non-redeemers, once we match the customers in these two groups. We calculate the percentage reduction in bias (PRB), proposed by Rosenbaum and Rubin (1983) as follows:

$$PRB_n = 1 - \left| \frac{\overline{X_R^{post}} - \overline{X_N^{post}}}{\overline{X_R^{pre}} - \overline{X_N^{pre}}} \right| \tag{2}$$

PRB compares the means of the explanatory variables in the redemption model (Eq. 1) for redeemers and non-redeemers before matching ($\overline{X_R^{Pre}}$ and $\overline{X_N^{Pre}}$ respectively) and after matching ($\overline{X_R^{Post}}$, $\overline{X_N^{Post}}$ respectively). A large PRB value shows a considerable reduction in bias once the customers in the two groups are matched.

Once we build a matched sample with good quality at each firm, we can pool the samples across all six firms to perform our analysis of search and purchase behavior.

<u>Main Model Development</u>

We estimate the post redemption model for a period of 8 weeks after redemption. In the dataset, we observe customers' search and purchase behavior for much longer than that (about 28 weeks on average). However, we chose to investigate customer behavior for 8 weeks post-redemption since the redemption effect may wear out as a customer's memory of redemption fades over time. We consider customer behavior for 8 weeks after redemption which is close to the average inter-purchase time of all customers before redemption.

For each individual i, we estimate two search models: search for promotions at the focal firm and average search for promotions across competing firms. A customer wants to search for promotions when the utility of search is positive. Therefore, we do not observe positive search for all customers (i.e. censored at 0). The limited dependent variable model is generally fitted using Tobit specification. To do this we run a random effects Tobit model on a customer's search using the following equation:

$$\begin{aligned} \text{Search}^{j}_{i,\,\text{post}} &= \alpha^{j}_{0i} + \alpha^{j}_{1}\ \text{Redeemer}^{j}_{i} + \alpha^{j}_{2}\ \text{Search}^{j}_{i,\,\text{pre}} + \alpha^{j}_{3}\ \text{Search\_Other}^{j}_{i,\,\text{pre}} + \alpha^{j}_{4}\ \text{Freq}^{j}_{i,\,\text{pre}} \\ &+ \alpha^{j}_{5}\ \text{Amount}^{j}_{i,\,\text{pre}} + \alpha^{j}_{6}\ \text{Freq\_Other}^{j}_{i,\,\text{pre}} + \alpha^{j}_{7}\ \text{Amount\_Other}^{j}_{i,\,\text{pre}} + \alpha^{j}_{8}\ \text{Tenure}_{i} + \sum_{k} \text{Firm\_FE}_{k} + \varepsilon^{j}_{i} \end{aligned} \tag{3}$$

where $\text{Search}^{j}_{i,\text{Post}}$ is log of customer i's number of search incidences for promotions (including rewards), at the focal firm post redemption, Redeemer is a binary variable with value = 1 if customer i is a redeemer and value = 0 if the customer has not redeemed a reward, Post indicates after redemption period and pre indicates before redemption period, Freq is log of the average purchase frequency per week, and Amount is log of the average weekly purchase amount, at the focal firm. Similarly, Search_Other, Freq_Other, and Amount_Other capture customers' average search and purchase across all other 5 firms, Tenure is the time (in weeks) since a customer has joined the app, Firm_FE are firms' dummy variables that control for the heterogeneity among firms, and ε is the random error term. Similarly, we estimate average search across all other 5 firms ($\text{Search\_Other}^{j}_{i,\text{Post}}$), using the same explanatory variables.

Then, we estimate four models of purchase behavior: Purchase frequency and average weekly spending at the focal firm and on averages across other firms. The customer decides to whether to make a purchase when the utility of purchase is positive. Some customers make no purchase at the focal firm and/or across other firms during the 8-week post-redemption period. To accommodate partial observability of purchase behavior we run Tobit models, using the following equations:

$$\begin{aligned} \text{Amount}^{j}_{i,\text{post}} &= \chi^{j}_{0i} + \chi^{j}_{1}\ \text{Redeemer}^{j}_{i} + \chi^{j}_{2}\ \text{Search}^{j}_{i,\,\text{post}} + \chi^{j}_{3}\ \text{Search\_Other}^{j}_{i,\,\text{post}} + \chi^{j}_{4}\,\text{Freq}^{j}_{i,\,\text{pre}} + \chi^{j}_{5}\ \text{Amount}^{j}_{i,\,\text{pre}} \\ &+ \chi^{j}_{6}\ \text{Freq\_Other}^{j}_{i,\,\text{pre}} + \chi^{j}_{7}\ \text{Amount\_Other}^{j}_{i,\,\text{pre}} + \chi^{j}_{8}\ \text{Tenure}_{i} + \sum_{k} \text{Firm\_FE}_{k} + \varepsilon^{j}_{i} \end{aligned} \tag{4a}$$

$$\text{Freq}^{j}_{i,post} = \chi^{j}_{0i} + \chi^{j}_{1}\ \text{Redeemer}^{j}_{\ i} + \chi^{j}_{2}\ \text{Search}^{\,j}_{\ i,\,post} + \chi^{j}_{3}\ \text{Search\_Other}^{j}_{\ i,\,post} + \chi^{j}_{4}\,\text{Freq}^{j}_{\ i,\,pre} + \chi^{j}_{5}\ \text{Amount}^{j}_{\ i,\,pre}$$
$$+ \chi^{j}_{6}\ \text{Freq\_Other}^{j}_{\ i,\,pre} + \chi^{j}_{7}\ \text{Amount\_Other}^{j}_{\ i,\,pre} + \chi^{j}_{8}\ \text{Tenure}_{\,i} + \sum_{k} \text{Firm\_FE}_{k} + \varepsilon^{j}_{i} \quad (4b)$$

where Amount $^{j}_{i,Post}$ is log of customer i’s average weekly spending at the focal firm after the redemption, Freq $^{j}_{i,Post}$ is log of is log of the average purchase frequency per week, Redeemer is a binary variable with value = 1 if customer i is a redeemer and value = 0 if the customer has not redeemed a reward, Post indicates after redemption period and pre indicates before redemption period, Search is log of the number of search incidences. Similarly, Search_Other, Freq_Other, and Amount_Other capture customers’ average search and purchase across all other 5 firms, Tenure is the time (in weeks) since a customer has joined the app, Firm_FE are firms’ dummy variables that control for the heterogeneity among firms, and ε is the random error term. Similarly, we can estimate average purchase frequency and purchase amount across all other 5 firms (Freq_Other $^{j}_{i,Post}$, Amount_Other $^{j}_{i,Post}$, respectively), using the same set of explanatory variables .

We note that while the data is structured in a way which only allows for 1 time period (post-redemption), we still can have multiple observations per customer (focal and competing firms for each of the six firms). Thus, we estimate all of the models with random effects to control for potential unobserved customer heterogeneity. We estimate all six models jointly using CMP, a user-written procedure in STATA, which fits seemingly unrelated regression models with various response types, including Tobit as we have for this case at (Roodman 2011). This will help us to gain efficiency in our estimation by taking into account the potential correlation of error terms across search and purchase models at the focal and competing firms.

Results

Propensity Score Matching

In order to estimate propensity scores, we run a redemption model (Eq.1) at the firm level for all firms. The results for redemption model are presented in Table 3.2 (See Table 3.2). As shown in the table, across all six firms the number of points that a customer has accumulated at a firm has significant effect on that customer's likelihood of redeeming a reward at that firm ($p < .001$). Average point stock across other firms is significant only at firm D ($P<0.05$). If a customer has accumulated more points across other firms, that customer is less likely to redeem a reward at firm D. However, this effect is non-significant for other 5 firms. Effect of tenure on redemption behavior is also non-significant across all six stores.

Note that some of the covariates have been dropped from models due to lack of variation in the value of that variable. For instance, consider the redemption model for firm B. At the time of redemption (or the expected time of redemption for non-redeemers) Firms C, D, E and F have already offered all of their reward options (2, 9, 5 and 4 reward options respectively). As a result, there is no variation in the number of rewards that are available at each firm across all customers. Therefore, these variables have no explanatory power and have been dropped from the model. Similarly, all customers had sufficient points to receive the minimum reward at Firm B at the time of redemption at Firm B. Therefore, the value of variable Distance_Min_Reward is 0 for all customers, and as a result this variable is dropped from the model.

Once we obtained propensity scores from the redemption models in Table 3.2, we matched redeemers and non-redeemers based on their propensity scores as describe in the "Methodology" section. Next, we evaluated the quality of matching (See Table 3.3). Table 3.3 presents the mean values of the explanatory variables in redemption model (Eq. 1). Before matching, we see that the mean values of the explanatory variables for redeemers and non-redeemers are considerably different for some variables, including point stock at the focal firms, average point stock across other firms and tenure. However, after matching the difference in mean values of covariates between redeemer and non-redeemer groups are much smaller and become non-significant for all covariates across all firms ($p > 0.01$).

Finally, Table 3.4 presents the percentage of reduction in bias (PRB) across all firms (See Table 3.4). As it is show in the table, there is considerable reduction in bias for most variables, specifically point stock at the focal firm, average point stock across other firms, and tenure.

Note that PRB is not applicable when there is no variation in a variable across customers, before and after matching. For instance, as discussed earlier, Firms B, C, D, and E have already offered all of their reward options at the time of redemption, so there is no variation in the number of rewards that are available to different groups of customers. Also note that when the mean value for redeemers and non-redeemers were not significantly different before matching, PRB may not be a relevant measure. Because the two groups have similar values, the bias is already negligible before matching. In such case, a small change in the difference in mean values of the two groups after matching may have big, even negative impact on PRB. For instance, if the difference in means of point stocks is .1 before matching and becomes .3 after matching, the difference in mean values for the two groups is still statistically non-significant after matching. However, the percentage reduction in bias is -200%. Therefore, we apply PRB measure in cases where the mean value of a covariate is significantly different across the two groups before matching, so that matching can have a meaningful effect on reducing the bias in the mean value of an explanatory variable. For such variables, as it is shown in Table 3.4, matching has considerably reduced the bias, which indicates good matching (Rosenbaum and Rubin 1983).

Therefore, both evaluation approaches indicate good matching of redeemers with non-redeemers in the final sample used in the estimation of the main models.

Hypothesis Testing

Next, we discuss the results of our search and purchase models (Eq. 3 and 4). The results of the estimation for search behavior models (Eq. 3) are presented in Table 3.5 (See Table 3.5). Reward redemption has positive and significant impact on a customer's future search at the focal firm ($p < .001$) and across other firms ($p < .001$).

The results of the estimation for the purchase behavior models (Eq. 4) are presented in Table 3.6 (See Table 3.6). The effect of redemption on a customer's frequency and amount of purchase is positive and significant ($p< .001$). This suggests that a customer who redeems a reward at the focal firm is more likely to visit that firm more often and has higher spending post-redemption than a customer who has not redeemed any reward at the focal firm. The effect of redemption on customers' purchase behaviors across other stores is positive and statistically significant ($p< .001$). Customers who have redeemed a reward at the focal firm visit competing firms more often as compared to non-redeemers, and spend more on average. However, the magnitude of difference in purchase behavior between redeemers and non-redeemers across other firms is much smaller than the difference in their purchase behavior at the focal firm.

Discussion

The results of analysis show that redeeming a reward has significant effect on customer's future search and purchase behavior at the focal firm and across competing firms. At the focal firm, redemption has a positive and significant effect on search behavior of redeemers, confirming H1a. This finding shows that obtaining a reward may increase a customer's sensitivity to promotions in general. Receiving a reward is a positive experience for a customer, so the customer may become more interested in reward options and search more often for potential rewards whether it is at the focal or competing firms. Regarding the purchase behavior, customers who redeem a reward visit the focal firm more frequently as compared to non-redeemers, confirming H1b and H1c respectively. These results provide empirical support for the positive effect of rewarded behavior mechanism. The reinforcing effect of redemption on future purchase incidence and purchase amount is considerable. A customer that does not redeem a reward will purchase less frequently from the firm and may eventually discard the points that the customer has accumulated at that firm. In such case, the customer will not utilize the benefits of the reward program. These findings suggest that a firm can enhance the effectiveness of its reward program by encouraging customers to redeem the rewards they have already accumulated (Dorotic et al. 2014).

Redeemers and non-redeemers also differ in their search and purchase behavior across competing firms. Customers who redeemed a reward at the focal firm search more across competing firms as compared to non-redeemers, confirming H2a. Those customers also visit competing firms more often, and have higher spending rate than customers who have not redeemed a reward yet, confirming H2b and H2c respectively. We argue that the depletion of point stock will decrease the point pressure effect at the focal firm. The customer no longer feels locked-in with that firm and can switch to another firm at a lower cost. This opens up an opportunity for variety seeking and exploring new options, at least for a short period post-redemption.

Does Purchase Rate before Redemption Matter?

Our analysis of customer search and purchase behavior showed that reward redemption plays an important role in customers' search and purchase behavior over time. Customers who redeem a reward at one firm have considerably higher purchase rate at that firm, as compared to customers who did not redeem any rewards. However, our analysis also showed that once a customer redeems a reward at the firm, the customer becomes more prone to the trial of competitors' offering and becomes more interested in rewards presented by the firm's competitors. Therefore, redeeming a reward can induce a customer behavior that is unfavorable to the focal firm. An important and relevant managerial question is how different groups of customers might behave differently after redeeming a reward.

In order to answer this question, we ran an exploratory analysis of redeemers' purchase and search behavior to investigate the effect on reward redemption on customer behavior. Here we only focus on redeemers in our sample. We see two different patterns of purchase among these customers prior to reward redemption. One group of customers makes frequent purchases and accumulate points at much higher pace. They also search more for promotions offered by the firm. The other group of customers makes less frequent purchase and it takes them longer to accumulate points before making a redemption. We classify customers as heavy and light users respectively, based on their pre-redemption purchase behavior. Customers with average weekly spending below the median were classified as light users and those with the above median spending were coded as heavy users. The pre- and post- purchase and search behavior of these two groups is summarized in Table 3.7 (See Table 3.7).

Prior to redeeming a reward, heavy users visit the store more often and accumulate points much faster than light users. They also redeem a reward much earlier, after about 11.6 weeks since they become a program member. For light users, it takes about 38 weeks to accumulate points before redeeming a reward. However, both groups spend about 60% of the points they have accumulated to redeem a reward.

Based on the pre-redemption purchase patterns it seems that heavy users are more loyal to the firm, and therefore a better target for receiving rewards from the firm. However, the purchase level of heavy users drops considerably after redemption ($6.96 decrease in average spending post-redemption). On the other hand, average spending of light users did not change significantly after redemption (only $.05 decrease in average spending per week post-redemption). These results show that receiving a reward has different effects on heavy and light users, and this difference is statistically significant (t-value=7.38; $p<0.01$). There are also differences in purchase frequency of heavy and light users. After redeeming a reward heavy users visit the store less often compared to their pre-redemption period (0.56 decrease in average purchase frequency per week post-redemption). However, light users visit the store as frequently as they did before redemption. The difference in average purchase frequency, pre- and post-redemption is statistically significant across heavy and light users (t-value=7.59; $p<0.01$). Figure 3.2a and 3.2b depicts the pre-and post-redemption purchase behavior of the two groups (See Figure 3.2a and 3.2b)

Point-pressure and reward-behavior effects a customer experiences can vary based on customers' redemption behavior. There is heterogeneity in number of points customers have at the time of redemption, and what rewards they choose to redeem. Redeeming a large reward depletes a customer's point stock more than redeeming a small reward. The portion of points left after redemption may impact a customer's decision about future purchases. However, receiving a large gift can induce greater rewarded behavior effect, which in turn leads to higher sense of appreciation and loyalty toward the firm (Bolton, Kannan, and Bramlett 2000; Taylor and Neslin 2005). In our sample both heavy and light users' groups on average redeem about 60% of their accumulated points. Therefore the point-pressure effect for future redemption opportunities seems to be similar across the two groups. On the other hand, light users receive smaller gifts on average as compared to heavy users (average reward size of 34.7 points for light users and 45.6 points for heavy users). Even though both groups feel the same level of point pressure effect for future redemption opportunities, it seems that redeeming a reward, even a much smaller reward, has higher positive impact on light customers as compared to heavy customers. Therefore, reward redemption can induce more positive change in the behavior of light users.

These findings are consistent with previous studies. For instance, Wansink's (2003) conjoint survey of brand managers and customers show that brand managers usually prefer to focus their loyalty programs on heavy users. However, loyalty programs that target light users can generate higher potential incremental sales. In addition, two separate studies of free ham and turkey reward programs at grocery stores reveal that rewards lead to higher increase in spending by causal shoppers who have lower purchase baseline (Lal and Bell 2003; Taylor and Neslin 2005). Finally, Liu's (2007) study of a convince store franchise shows that loyalty program does not change the behavior of heavy users; however it makes light users to purchase more over time and become more loyal to the firm.

Implications to Theory and Practice

<u>Implications to Theory</u>

Our study aims to better understanding of a customer usage of loyalty program (i.e. reward redemption) across firms. We show that reward redemption at one firm has positive impact on that customer's future search and purchase at the firm. This finding provides empirical support for the reinforcing effect of the rewarded behavior mechanism (Dorotic et al. 2014; Lewis 2004; Drèze and Nunes 2011; Taylor and Neslin 2005). We also show that reward redemption at the focal firm has signifcant effect on the customer's future search and purchase behavior across competing firms. In other words, our study reveals that there is a spillover effect in a customer's behavior across loyalty programs across firms. This has significant implication to theory. It is impossible to demonstrate the cross-firm effect of reward redemption without observing a customer's purchase and redemption behavior across firms. Our novel dataset allows us to observe a customer's interaction across competing firms, and therefore we could provide evidence for the cross-firm effect of reward redemption. Our analysis shows that redemption of reward decreases point pressure effect, and consequently increases purchase across other firms.

Implications to Practice

From the practical standpoint, the findings from of our study can help guide the design of loyalty programs and reward thresholds. Some firms set a high threshold for rewards, so that a customer has to spend higher amount to become eligible for a reward. However, our empirical analysis shows that once a customer redeems a reward at a given firm, that customer revisits the firm more often and spends more on average as compared to a customer who has not redeemed any reward. A customer that does not redeem a reward may eventually discard the points and switch to a competitor that offers more attractive reward options. Thus, stimulating reward redemption is a means to enhance customer loyalty.

The rewarded behavior effect reinforces future purchase. However, redemption of a reward weakens the point pressure effect. In the absence of point pressure, we empirically show that a customer is more likely to search for and try products from competitors. Thus, managers need to consider this trade-offs between rewarded behavior effect and point pressure effect when designing and implementing a loyalty reward program. The reward program needs to be designed in a way that enhances rewarded behavior effect, while having a mechanism in place to minimize the negative effect of point pressure reduction post-redemption.

Limitations and Future Research

We do acknowledge the limitations of our study. Our study is conducted using firms in the restaurant industry. This may limit the generalizability of the findings of the study to other industries. For instance in some industries, the rewarded behavior effect may have less impact on future customer purchase behavior when customers make infrequent and large purchases (e.g. airline industry). This might also lead to a more significant point pressure effect given the high point redemption levels (e.g. a free flight). Even though the context of our study is with firms with high frequency lower value transactions, we believe the key takeaways of our study will likely hold, i.e. firms need to pay attention to the trade-off between the point pressure effect and rewarded behavior effect when creating and implementing a loyalty program in a competitive market.

We also did not consider the impact of price and product variety on customer choice. We purposefully focused on restaurants that offer fairly similar menu at a close price range, so that customer price sensitivity and variety seeking do not confound the findings of our study. Future studies should consider how price and product variety among competing firms might impact a customer's search and purchase behavior across firms.

There are some additional avenues to pursue for future research. First, it is important to incorporate a larger sample which includes more firms and customers to improve the reliability of our findings. As a robustness check, it is important to replicate the study in other geographic markets. Second, future research could investigate how customer heterogeneity may affect customer responsiveness to reward redemption. Prior research has shown that different segments (e.g. light vs. heavy users, price-oriented vs. service-oriented) respond differently to reward programs (Bell and Lal 2003, Kopalle et al. 2012; Taylor and Neslin 2005). It would be insightful to see if there are significant differences in the search and purchase behavior of different segments across other firms as well, both pre- and post-redemption.

In summary, the contribution of our study is threefold. First, we investigate the effect of reward redemption on a customer behavior at the focal firm, controlling for that customer's interaction across competing firms. We empirically show that rewarded behavior mechanism has significant reinforcing effect on the customer's future search and purchase at the focal firm. Second, we show that the customer's reward redemption at the focal firm spills over onto that customer's search and purchase behavior across competing firms. To our knowledge, this is the first study that looks at the cross-firm effect of reward redemption, a key contribution to the marketing literature. Third, our analysis of redeemers' post-redemption behavior reveals that redeeming a reward has much more positive effect on light users as compared to heavy users. This finding suggests that in order to increase the return on investment in loyalty programs, firms should not focus their reward programs solely on their most frequent customers. Rewarding the less frequent customers seems to provide higher return for firm and leads to greater behavioral change for customers.

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TABLE 3.1: Descriptive statistics

Variable	Redeemers		Non-redeemers	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Customer Behavior				
Number of Transactions (per month)	2.49	2.61	0.55	0.99
Spending (per month)	19.56	17.73	5.30	7.25
Search (per month)	0.26	0.45	0.06	0.18
Redemption				
Redeemer (%)	34%	NA	66%	NA
Point Stock (at time of redemption) *	77.07	47.79	23.66	21.53
Average Point Stock at Other Firms (at time of redemption) *	4.42	11.57	3.39	8.98
Control Variable				
Tenure (in months at time of redemption)*	6.35	4.98	7.01	4.69

* for non-redeemers, expected redemption time is used as time of redemption

TABLE 3.2: Results of redemption models

Variables	Business A	Business B	Business C	Business D	Business E	Business F
	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
Intercept	1.970 (2.397)	-2.054 (0.914) *	-3.969 (1.263) **	-1.446 (1.449)	-2.054 (0.914) *	-0.571 (1.852)
Point_Stock	0.050 (0.005) ***	0.035 (0.006) ***	0.044 (0.007) ***	0.047 (0.008) ***	0.035 (0.006) ***	0.038 (0.005) ***
Point_Stovck_Other	0.008 (0.024)	0.019 (0.013)	-0.017 (0.019)	-0.037 (0.015) *	0.019 (0.013)	-0.010 (0.013)
Tenure (weeks)	0.003 (0.005)	-0.014 (0.011)	0.008 (0.011)	0.007 (0.010)	-0.004 (0.008)	0.007 (0.007)
Biz A_Rewards	0.051 (0.424)	-0.210 (0.430)	-0.356 (0.606)	-0.095 (0.682)	-0.210 (0.430)	-1.163 (0.428) **
Biz B_Rewards	-0.230 (0.065) ***	0.063 (0.079)	-[a]	-0.329 (0.130) *	0.063 (0.079)	-0.117 (0.083)
Biz C_Rewards	0.025 (0.525)	-[a]	-[a]	-[a]	-[a]	-0.197 (0.886)
Biz D_Rewards	0.088 (0.146)	-[a]	-[a]	-[a]	-[a]	-[a]
Biz E_Rewards	-1.220 (0.445) **	-[a]	-[a]	-[a]	-[a]	-[a]
Biz F_Rewards	-[a]	-[a]	-[a]	-[a]	-[a]	-[a]
Distance_Min_Reward	-0.113 (0.062)	-[a]	-[a]	-[a]	-[a]	-[a]

[a] There is no variation in this variable across all customers, and therefore this variable is dropped from the equation.

* Significant at p-value < 0.05; ** Significant at p-value < 0.01; *** Significant at p-value < 0.

TABLE 3.3: Means of covariates in matched vs. unmatched samples

Business A				
Covariates	**Unmatched**		**Matched**	
	Non-redeemer (N=539)	**Redeemer (N= 215)**	**Non-redeemer (N= 150)**	**Redeemer (N= 150)**
Point	27.86	73.45	53.60	59.70
Point_Other Firms	1.59	2.52	2.55	2.76
Tenure (Weeks)	29.15	29.72	28.76	30.60
Biz A_Rewards	2.05	2.10	2.05	2.04
Biz B_Rewards	2.95	2.36	2.61	2.61
Biz C_Rewards	1.82	1.76	1.87	1.89
Biz D_Rewards	8.32	8.08	8.52	8.64
Biz E_Rewards	4.99	4.68	4.96	4.99
Biz F_Rewards	4	3.94	4	4
Biz A_Distance Min Reward	3.84	0	0.09	0
Biz B_Distance Min Reward	9.44	9.13	9.43	9.06
Biz C_Distance Min Reward	14.11	13.75	13.97	14.09
Biz D_Distance Min Reward	19.51	17.48	19.15	17.61
Biz E_Distance Min Reward	9.19	9.07	9.08	9.04
Biz F_Distance Min Reward	13.36	14.92	14.17	13.98

Business B				
Covariates	**Unmatched**		**Matched**	
	Non-redeemer (N=262)	**Redeemer (N= 101)**	**Non-redeemer (N= 53)**	**Redeemer (N= 53)**
Point	21.23	71.98	44.81	52.09
Point_Other Firms	3.55	1.87	4.05	2.36
Tenure (Weeks)	26.38	20.22	19.74	20.27
Biz A_Rewards	2.06	1.98	2.04	2.02
Biz B_Rewards	4	4	4	4
Biz C_Rewards	2	2	2	2
Biz D_Rewards	9	9	9	9
Biz E_Rewards	5	5	5	5
Biz F_Rewards	4	4	4	4
Biz A_Distance Min Reward	11.55	14.62	9.68	13.57
Biz B_Distance Min Reward	0.75	0	0	0
Biz C_Distance Min Reward	13.49	14.36	13.26	13.78
Biz D_Distance Min Reward	19.36	20.05	19.37	20.38
Biz E_Distance Min Reward	9.32	9.60	9.81	9.62
Biz F_Distance Min Reward	9.39	9.50	9.06	9.43

Business C				
Covariates	Unmatched		Matched	
	Non-redeemer (N=269)	**Redeemer (N= 65)**	**Non-redeemer (N= 46)**	**Redeemer (N= 46)**
Point	29.23	100.16	70.65	84.83
Point_Other Firms	4.26	4.58	3.99	3.66
Tenure (Weeks)	33.66	30.34	31.39	32.54
Biz A_Rewards	1.94	2.00	1.96	1.96
Biz B_Rewards	4	3.38	4	4
Biz C_Rewards	2	2	2	2
Biz D_Rewards	9	9	9	9
Biz E_Rewards	5	5	5	5
Biz F_Rewards	4	4	4	4
Biz A_Distance Min Reward	15.27	15.63	15.07	14.90
Biz B_Distance Min Reward	9.48	8.92	9.58	8.92
Biz C_Distance Min Reward	2.07	0	0	0
Biz D_Distance Min Reward	19.32	20.12	19.63	20.21
Biz E_Distance Min Reward	9.18	9.23	8.32	9.13
Biz F_Distance Min Reward	9.22	10.78	8.71	8.27

Business D				
Covariates	Unmatched		Matched	
	Non-redeemer (N=291)	**Redeemer (N= 103)**	**Non-redeemer (N=57)**	**Redeemer (N=57)**
Point	18.51	83.08	47.10	54.61
Point_Other Firms	5.37	8.22	6.70	5.55
Tenure (Weeks)	29.02	26.14	28.05	26.72
Biz A_Rewards	1.98	2.00	1.98	2.00
Biz B_Rewards	3.51	2.91	3.37	3.37
Biz C_Rewards	2	2	2	2
Biz D_Rewards	9	9	9	9
Biz E_Rewards	5	5	5	5
Biz F_Rewards	4	4	4	4
Biz A_Distance Min Reward	13.18	13.51	10.53	11.52
Biz B_Distance Min Reward	9.41	9.33	9.27	9.17
Biz C_Distance Min Reward	14.18	14.19	13.94	13.98
Biz D_Distance Min Reward	8.02	0	0	0
Biz E_Distance Min Reward	8.59	8.28	9.17	8.21
Biz F_Distance Min Reward	11.10	13.50	11.41	12.02

Business E				
Covariates	Unmatched		Matched	
	Non-redeemer (N=323)	Redeemer (N=110)	Non-redeemer (N=87)	Redeemer (N=87)
Point	18.61	69.56	38.92	46.05
Point_Other Firms	2.90	4.40	4.89	5.46
Tenure (Weeks)	22.87	19.60	19.61	20.91
Biz A_Rewards	1.98	1.98	1.94	1.98
Biz B_Rewards	2.76	2.40	2.85	2.71
Biz C_Rewards	2	1.85	2	2
Biz D_Rewards	9	8.51	9	9
Biz E_Rewards	5	4.98	5	5
Biz F_Rewards	4	4	4	4
Biz A_Distance Min Reward	18.07	17.81	17.09	15.59
Biz B_Distance Min Reward	9.53	9.30	9.22	9.21
Biz C_Distance Min Reward	14.12	15.00	13.90	15.00
Biz D_Distance Min Reward	19.36	18.94	18.62	18.68
Biz E_Distance Min Reward	1.70	0	0	0
Biz F_Distance Min Reward	13.84	15.23	13.28	14.25

Business F				
Covariates	Unmatched		Matched	
	Non-redeemer (N=280)	Redeemer (N= 165)	Non-redeemer (N= 111)	Redeemer (N= 111)
Point	41.01	98.96	64.08	72.53
Point_Other Firms	3.00	3.44	3.28	3.23
Tenure (Weeks)	27.18	24.54	26.79	26.83
Biz A_Rewards	2.03	2.01	1.99	1.97
Biz B_Rewards	3.26	2.88	3.17	3.17
Biz C_Rewards	1.99	1.84	1.98	1.98
Biz D_Rewards	9	8.35	9	9
Biz E_Rewards	5	4.84	5	5
Biz F_Rewards	4	4	4	4
Biz A_Distance Min Reward	15.14	17.38	16.54	17.17
Biz B_Distance Min Reward	9.50	9.52	8.98	9.65
Biz C_Distance Min Reward	13.92	14.40	13.62	14.50
Biz D_Distance Min Reward	20.03	20.40	19.59	20.55
Biz E_Distance Min Reward	9.50	9.45	9.16	9.65
Biz F_Distance Min Reward	0.56	0	0	0

TABLE 3.4: Percentage reduction in bias (PRB) after matching

Covariates	Percentage Reduction in Bias (%)					
	Business A	Business B	Business C	Business D	Business E	Business F
Point	86.7	83.7	77.7	81.8	84.1	84.4
Point_Other	77.7	12.1 [c]	45.3 [c]	-71.2 [c]	63.9	92.5
Tenure (Weeks)	-19.1 [c]	91.8	-93.5 [c]	-705 [c]	-38.2 [c]	96.7
Biz A_Rewards	72.2	74.9	100	55	-161.6 [c]	67.4
Biz B_Rewards	100	. [a]	. [b]	100	-143.8 [c]	100
Biz C_Rewards	31.4 [c]	. [a]	. [a]	. [a]	. [b]	100
Biz D_Rewards	1.6 [c]	. [a]	. [a]	. [a]	. [b]	. [b]
Biz E_Rewards	88.8	. [a]	. [a]	. [a]	. [b]	. [b]
Biz F_Rewards	. [b]	. [a]	. [a]	. [a]	. [a]	. [a]
Distance Min Reward	95.4	. [b]	. [b]	. [b]	. [b]	. [b]

[a] The variable has similar value for all customers before matching (zero variance)

[b] The variable has similar value for all customers once matched (zero variance)

[c] The mean value for redeemers and non-redeemers were not significantly different before matching.

TABLE 3.5: Results for search behavior model

Search Behavior	**Search for Promotions**	**Search for Promotions**
	Own-effect	**Cross-effect**
Variables	**Coeff. (Std. Err.)**	**Coeff. (Std. Err.)**
Intercept	-0.500 (0.131) ***	-0.602 (0.151) ***
Redeemer	0.365 (0.058) ***	0.210 (0.052) ***
Purchase Behavior		
Freq $_{Pre}$	-0.110 (0.111)	-0.010 (0.153)
Freq_Other $_{Pre}$	-0.244 (0.152)	0.042 (0.119)
Spending $_{Pre}$	-0.069 (0.057)	-0.162 (0.067) *
Spending_Other $_{Pre}$	0.079 (0.043)	0.186 (0.042) ***
Search Behavior		
Search_Promo $_{Pre}$	0.808 (0.116) ***	0.221 (0.177)
Search_Promo_Other $_{Pre}$	-0.112 (0.173)	0.209 (0.180)
Control Variables		
Tenure	-0.002 (0.002)	0.000 (0.002)
Firm Fixed Effects	Included	Included
Model Fit [a] Log Likelihood	-1,318.3428	

* Significant at p-value < 0.05; ** Significant at p-value < 0.01; *** Significant at p-value < 0.

[a] Model fit for joint estimation of all 6 models (search and purchase)

TABLE 3.6: Results for purchase behavior models

Purchase Behavior	**Purchase Frequency**	**Spending**	**Purchase Frequency**	**Spending**
	Own-effect	**Own-effect**	**Cross-effect**	**Cross-effect**
Variables	**Coeff. (Std. Err.)**	**Coeff. (Std. Err.)**	**Coeff. (Std. Err.)**	**Coeff. (Std. Err.)**
Intercept	-0.192 (0.084) *	-1.067 (0.276) ***	-0.105 (0.045) *	-1.794 (0.424) ***
Redeemer	0.315 (0.032) ***	0.965 (0.104) ***	0.122 (0.017) ***	0.668 (0.155) ***
Purchase Behavior				
$Freq_{Pre}$	0.567 (0.074) ***	0.282 (0.244)	0.083 (0.040) *	0.180 (0.379)
$Freq\_Other_{Pre}$	-0.095 (0.105)	0.236 (0.288)	0.445 (0.052) ***	0.572 (0.415)
$Spending_{Pre}$	-0.126 (0.038) ***	-0.018 (0.120)	-0.050 (0.021) *	-0.293 (0.187)
$Spending\_Other_{Pre}$	0.003 (0.031)	0.359 (0.094) ***	0.015 (0.016)	1.095 (0.143) ***
Search Behavior				
$Search\_Promo_{Post}$	-0.264 (0.222)	-0.571 (0.732)	-0.116 (0.140)	-0.606 (1.115)
$Search\_Promo\_Other_{Post}$	0.637 (0.445)	-0.870 (1.148)	0.864 (0.180) ***	-2.997 (1.439) *
Control Variables				
Tenure	-0.002 (0.001)	-0.003 (0.004)	-0.001 (0.001)	0.005 (0.005)
Firm Fixed Effects	Included	Included	Included	Included
Model Fit[a] Log Likelihood	-1,318.3428			

* Significant at p-value < 0.05; ** Significant at p-value < 0.01; *** Significant at p-value < 0.001

[a] Model fit for joint estimation of all 6 models (search and purchase)

TABLE 3.7: Purchase and search behavior of redeemers

	Light Users	Heavy Users	Total Sample
Sample Size	251	253	504
Purchase Behavior			
Spending, Pre-redemption	1.78	11.91	6.86
Spending, Post-redemption	1.73	4.95	3.35
Mean Difference Test	Diff= -6.91, t=-7.38		
Purchase Frequency, Pre-redemption	.21	1.06	.63
Purchase Frequency, Post-redemption	.20	.5	.35
Mean Difference Test	Diff=-.56, t=-7.59		
Search Behavior			
Search, Pre-redemption	.04	.15	.09
Search, Post redemption	.02	.04	0.3
Mean Difference Test	Diff=-.08, t=-3.88		
Redemption Behavior			
Time to redeem a reward (weeks)	38.0	11.6	24.8
Point Stock at Time of Redemption	52.44	73.30	62.87
Reward Size	34.70	45.64	40.17
Redemption Ratio (% points redeemed)	0.65	0.62	0.64

Figure 3.1a: Model free evidence: average inter-purchase time at the focal firm in weeks (SD) before and after redemption

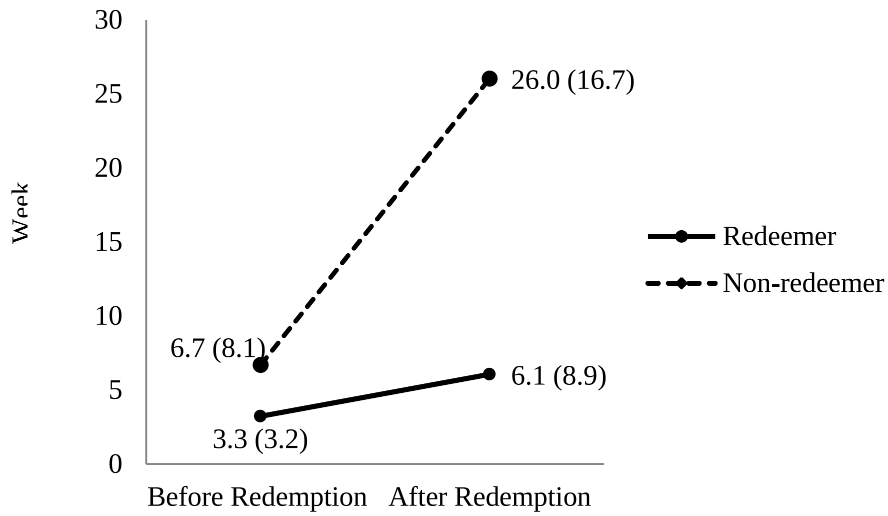


Figure 3.1b: Model free evidence: average inter-purchase time at other firms in weeks (SD) before and after redemption

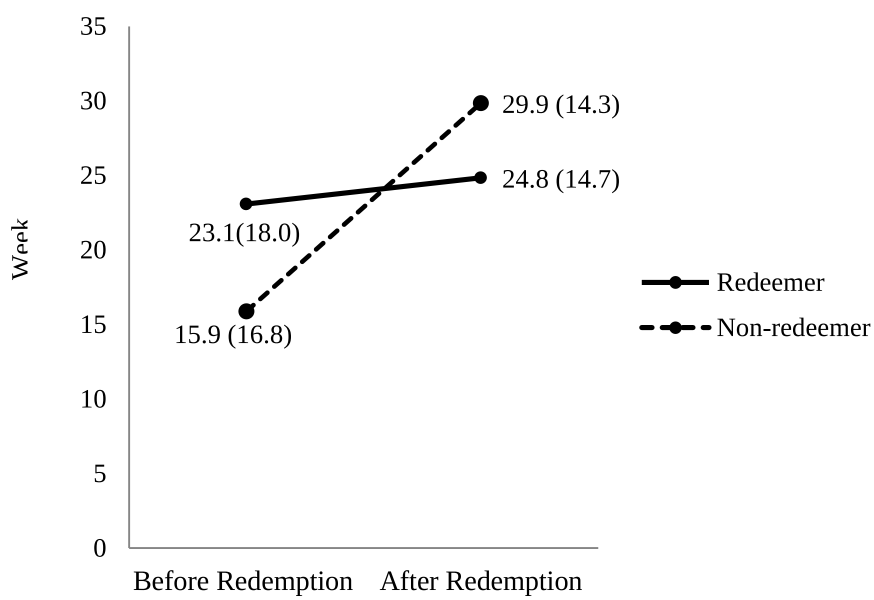


Figure 3.2a Average purchase frequency per week, before and after redemption

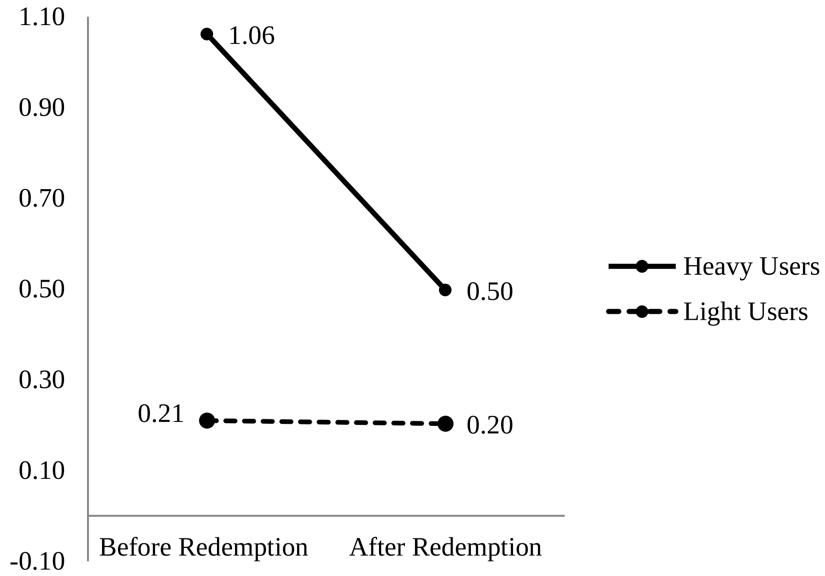
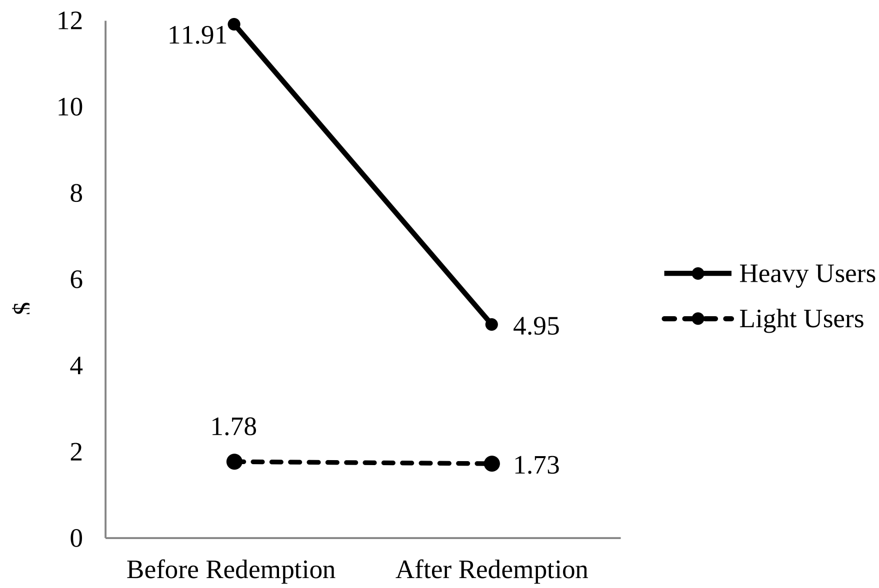


Figure 3.2b: Average spending per week, before and after redemption



CHAPTER 4: CONCLUSION

In summary, the two essays in this dissertation have been designed to examine different aspects of relationship marketing that has not been thoroughly investigated previously. In the first essay (see Chapter 2), I argue that breadth of relationship has significant impact on relationship's outcomes. In a non-profit setting, I empirically show that donors who develop a broader relationship with a non-profit are more valuable to that non-profit over time. They have higher future value for the organization, have lower volatility in their relationships with the organization and are more responsive to marketing communications. I also show that the proposed measure of relationship breadth is better able to capture the variation in giving amount and more accurately predicts the expected giving amount (both in-sample and out-of-sample) than the measure of cross-donation (i.e. number of causes a donor supports).This finding contributes to the literature on measurements of the breadth of customer relationships. It suggests that measures such as cross-buy (i.e. number of product categories purchase), commonly used in the customer relationship management literature to measure the breadth of a relationship, could be enhanced by also capturing the distribution of purchases.

In addition, in Essay 1 I show that drivers of relationship change over the donor life cycle. At the acquisition phase, intrinsic factors drive the breadth of relationship, while at the retention phase extrinsic factors have higher impact on driving the breadth of relationship. Based on these findings, I recommend that at the acquisition phase, nonprofit organizations should align donors with causes that are "close to the heart". Later at the retention phase, marketing efforts should be focused on encouraging donors to increase the breadth of their relationship with the organization by giving to additional causes. Finally, the field study conducted at the focal nonprofit provides causal evidence that marketing communications can motivate donors to broaden their relationships with the organization.

In the second essay (see Chapter 3) I focus on reward programs, which are one of the most common relationship marketing strategies across industries. I investigate the effect of reward redemption on a customer behavior at a firm, controlling for that customer's relationship across competing firms. I empirically show that customer's reward redemption at a firm not only affects customer's future search and purchase at the focal form, but the redemption effect also spills over onto that customer's search and purchase behavior across competing firms. In addition, my analysis of post-redemption behavior of customers shows that return on investment on relationship marketing is not higher for best, most loyal customers. For light users it takes more time to accumulate points to redeem a reward. However, reward redemption has much more positive effect on light users as compared to heavy user. This finding suggest that a firm might benefit more from its reward program if it encourages light users to redeem a reward sooner and delay the redemption for heavy users, or offer them higher reward options.

I hope that this dissertation inspires future studies on relationship marketing, and can help researchers and practitioners to better understand drivers of relationship marketing and its impacts on customer behavior in a competitive environment.

APPENDIX 2.A: REVIEW OF SIMILAR STUDIES

Study	Empirical Analysis	Drivers and Consequences of Targeted Giving		Key Insights
		Drivers	Consequences	
Null (2011)	Experiments	Warm glow utility, Risk aversion	Inefficient charitable giving	Most subjects simultaneously gave to multiple charities with similar missions even when the social benefits of gifts to different charities were not equal. Warm glow and risk aversion both seem to be important determinants of the inefficiencies that arise from donors' choices about which charities to support.
Bennett (2012)	Survey	Emotional satisfaction; Intrinsic need for variation; Cognitive Balance	X	Donors who gave to organizations within the same sector gained less emotional benefit from donating to the second charity than they obtained from giving to the main charity. Innate desire for variation and the desire to obtain cognitive balance significantly influences the likelihood that a person's main and second charities would be in different sectors.
Robinson et al. (2012)	Experiments & Field Study	Customer Collectivism; Perceptual fit between company and a cause; Perception of personal role	Willingness to pay for a product associated with a cause	The positive effect of allowing consumers to select the cause in a CM campaign on consumer reactions to products associated with CM campaigns is moderated by customer collectivism and perceptual fit between company and a cause, and is mediated by enhanced perceptions of personal role in helping the cause.
Ly & Mason (2012)	Secondary data (Aggregate level)	X	X	Authors presents evidence on the relative popularity of competing development projects on Kiva.org
Li et al. (2013) working paper	Experiments	X	Likelihood and Amount of gifts	For both government and private charities, the amount of voluntary contributions and the likelihood of voluntarily giving are significantly higher for organizations with targeted causes than to general funds. The impact of targeting is significantly greater for government organizations.
Batista et al. (2013) working paper	Experiment	X	Amount of gift	Utility of givers depends on the composition (not just the level) of gift-recipient expenditures, and givers thus seek control over transferred resources. Dictators share more with counterparts when they have the option of giving in kind (in the form of goods), compared to giving that must be in cash.
Eckel et al. (2014) working paper	Field Study	X	Amount of gift	While there is no effect on the probability of giving, donations are significantly larger when there is the option of directing
This study	Secondary data (Donor level) & Field Study	Intrinsic and Extrinsic motivators	Likelihood and Amount of gifts	Giving to multiple causes in the past (higher *Donation Variety)* increases the likelihood the donor makes a subsequent donation and on average donation amount would be higher and sensitivity to negative macroeconomic shocks would be lower. In the acquisition phase, most donors give to a single initiative and the decision is influenced more by a donor's intrinsic motivation. In The retention phase, nonprofit marketing efforts have a more significant influence on a donor's decision to give to multiple initiatives.

APPENDIX 2.B: INSTRUMENTAL VARIABLE MODEL AND ESTIMATION

To empirically test our hypotheses, we first control for the endogeneity of marketing efforts using instrumental variables. We need to identify at least two instrumental variables which are likely to impact the nonprofit organization's decision to expend marketing efforts, but unlikely to impact a given donor's expected gift amount. We identify two instrumental variables we believe are related to the level of marketing efforts, but unrelated to gift amount: (1) Total budget for personal marketing efforts and (2) Total budget for impersonal marketing efforts. We expect that that increases (decreases) in the marketing budget is likely to lead to increases (decreases) in average spending levels across donors, but unlikely to improve the targeting of the marketing efforts to specific donors which increase gift amount. Thus, we believe that these two variables will act as good instruments to handle the potential endogeneity problem inherent in the strategic allocation of marketing efforts. We also include a donor's past giving amount and time since graduation (not instruments since they is also included in the main equation) and interactions between the instruments and past giving amount and time since graduation as we expect these will impact the amount of marketing efforts expended by the university foundation.

We estimate the instrumental variable model for both personal and impersonal marketing efforts and use a control function approach (Petrin and Train 2010) to include marketing efforts (both personal and impersonal) into the next step of analysis, along with the computed error from the instrumental variable equations. This model takes the following format:

$$\begin{aligned} \mathrm{PerMktg}_{i,t} = \; & \alpha_0 + \alpha_1 \ln(\mathrm{PerMktgBudg}_t) + \alpha_2 \ln(\mathrm{ImpMktgBudg}_t) + \alpha_3 \ln(\mathrm{Gift}_{i,t-1}) + \alpha_4\, \mathrm{TSG}_{i,t-1} + \\ & \alpha_5 \ln(\mathrm{PerMktgBudg}_t) \times \ln(\mathrm{Gift}_{i,t-1}) + \alpha_6 \ln(\mathrm{PerMktgBudg}_t) \times \mathrm{TSG}_{i,t-1} \\ & \alpha_7 \ln(\mathrm{ImpMktgBudg}_t) \times \mathrm{c} + \alpha_8 \ln(\mathrm{ImpMktgBudg}_t) \times \mathrm{TSG}_{i,t-1} + \mathrm{c}_{i1} + \varepsilon_{i,t1} \end{aligned} \tag{B1}$$

$$
\begin{aligned}
\mathrm{ImpMktg}_{i,t} = \; & \beta_0 + \beta_1 \ln(\mathrm{PerMktgBudg}_t) + \beta_2 \ln(\mathrm{ImpMktgBudg}_t) + \beta_3 \ln(\mathrm{Gift}_{i,t-1}) + \beta_4 \, \mathrm{TSG}_{i,t-1} \\
& + \beta_5 \ln(\mathrm{PerMktgBudg}_t) \times \ln(\mathrm{Gift}_{i,t-1}) + \beta_6 \ln(\mathrm{PerMktgBudg}_t) \times \mathrm{TSG}_{i,t-1} \\
& \beta_7 \ln(\mathrm{ImpMktgBudg}_t) \times \ln(\mathrm{Gift}_{i,t-1}) + \beta_8 \ln(\mathrm{ImpMktgBudg}_t) \times \mathrm{TSG}_{i,t-1} + c_{i2} + \varepsilon_{i,t2} \quad \text{(B2)}
\end{aligned}
$$

where $\mathrm{PerMktg}_{i,t}$ ($\mathrm{ImpMktg}_{i,t}$) is the marketing expenditure on personal (impersonal) marketing efforts for donor i at time t, $\ln(\mathrm{PerMktgBudg}_t)$ ($\ln(\mathrm{ImpMktgBudg}_t)$) is the log of the total marketing budget used for personal (impersonal) marketing efforts by the nonprofit foundation in time t, $\ln(\mathrm{Gift}_{i,t-1})$ is the log of the gift amount given by donor i at time t-1, $\mathrm{TSG}_{i,t-1}$ is the time since graduation by donor i up to time t-1, c_{i1} and c_{i2} are random effects which control for the unobserved heterogeneity of donor i, and $\varepsilon_{i,t1}$, $\varepsilon_{i,t2}$ are random error terms. We estimate the model for both personal and impersonal marketing efforts using a random effects linear regression and use the control function approach to include marketing efforts into the next step of analysis (i.e. using the computed error terms and from the marketing expenditure models along with the actual marketing expenditure values). As a robustness check we also estimate the main model of expected donation amount on the 2 instrumental variables. We find that the 2 instruments are unrelated to expected giving. This makes them useful instrumental variables for our modeling framework.

Robustness Checks

There are two general conditions by which you can test the quality of your instruments in your instrumental variable regression. First, you want your instruments to be partially correlated with the endogenous variables, in this case impersonal and personal marketing efforts. To do this we estimate the instrumental variable regressions (see Table 2.B1).

TABLE 2.B1: Results for the instrumental variable models

Variable	DV = $PerMktg_{it}$ Coefficient (Std. Err.)	DV = $ImpMktg_{it}$ Coefficient (Std. Err.)
Intercept	1.562 (0.516)*	0.433 (0.069)*
$\ln(PerMktgBudg_t)$	0.281 (0.027)*	0.351 (0.036)*
$\ln(ImpMktgBudg_t)$	-0.781 (0.768)	1.314 (0.112)*
$\ln(Gift_{i,t-1})$	0.338 (0.092)*	0.038 (0.011)*
$Tenure_{i,t-1}$	0.032 (0.096)	0.010 (0.002)*
$\ln(PerMktgBudg_t) * \ln(Gift_{i,t-1})$	0.550 (0.066)*	0.045 (0.010)*
$\ln(ImpMktgBudg_t) * \ln(Gift_{i,t-1})$	0.102 (0.135)	0.082 (0.020)*
$\ln(PerMktgBudg_t) * Tenure_{i,t-1}$	0.062 (0.005)*	-0.038 (0.008)*
$\ln(ImpMktgBudg_t) * Tenure_{i,t-1}$	-0.011 (0.075)	0.073 (0.011)*
Model Fit (R^2)	**0.286**	**0.593**

* Significant at *p*-value < 0.01

We can see from Table 2.B1 that the instruments are correlated with the endogenous marketing effort variables (i.e. they are significant predictors of impersonal and personal marketing efforts). Specifically, we find as the marketing budget increases, donors receive more personal and impersonal marketing efforts from the foundation. However, personal marketing is based mainly on donors who gave larger gifts in the past, while impersonal marketing is based mainly on a donor's time since graduation. While the personal marketing budget only affects personal marketing, impersonal marketing is affected by both personal and impersonal marketing budgets. A possible explanation is that a greater portion of a marketing budget is devoted to personal marketing, which is more costly as compared to impersonal marketing, but it is aimed at potential future major donors who are likely to make gifts of larger value. Once the foundation takes care of its major contributors, the rest of marketing budget will be allocated to impersonal marketing efforts. Both the personal and impersonal marketing instrumental variable models show a reasonable fit (R2 is 0.286 and 0.593 for personal and impersonal marketing models respectively). Second, you want the instruments to be generally unrelated to the main outcome variable. It is not straightforward in this case to run a simple correlation between two instruments (Personal Marketing Budget, Impersonal Marketing Budget, and Tenure) and the outcome variables of interest (*Donation Variety* and Donation Amount). This is due to the fact that the main outcome variables are both censored at 0. Thus, to test whether the instruments are related to the outcome variable of interest, we do the following. We use the same dynamic panel estimation procedure as is described in the main paper to estimate a model with only the lag of the dependent variable and the variables from the instrumental variable regressions. We start by estimating the model for Donation Amount (see Table 2.B2).

We see from Table 2.B2 that the lag of the dependent variable is significant in this estimation. Further, we see that the interaction between the lag of the dependent variable and the two marketing budget variables are significant in the main equation. We also see that that interaction between the variable time since graduation and the two marketing budget variables are significant across both equations. However, we see that two instrumental variables are not significant in either equation and the interaction between the two instrumental variables and the lag of the dependent variable are not significant in the selection equation. This provides some empirical evidence that the instruments of Personal Marketing Budget and Impersonal Marketing Budget are good instruments for the Donation Amount model.

TABLE 2.B2: Instrumental variables regressed on donation amount

Variables (DV = Donation Amount)	**Selection Coeff. (Std. Err.)**	**Main Coeff. (Std. Err.)**
Intercept	0.411 (0.033)*	2.918 (0.039)*
$\ln(Gift_{i,t-1})$	0.214 (0.003)*	0.272 (0.006)*
$\ln(PerMktgBudg_t)$	0.233 (0.597)n/s	0.099 (0.091)n/s
$\ln(ImpMktgBudg_t)$	0.315 (0.213)n/s	0.046 (0.032)n/s
$TSG_{i,t-1}$	-0.181 (0.005)*	0.008 (0.004)**
$\ln(PerMktgBudg_t) * \ln(Gift_{i,t-1})$	0.00004 (0.00005)n/s	0.00001 (0.000001)*
$\ln(ImpMktgBudg_t) * \ln(Gift_{i,t-1})$	0.00001 (0.00001)n/s	0.0001 (0.00001)*
$\ln(PerMktgBudg_t) * TSG_{i,t-1}$	0.044 (0.001)*	0.011 (0.001)*
$\ln(ImpMktgBudg_t) * TSG_{i,t-1}$	-0.048 (0.002)*	-0.022 (0.002)*
Model Fit		
Log Pseudolikelihood	-108,426.32	

* Significant at p-value < 0.01; ** Significant at p-value < 0.05; n/s Not significant at p-value < 0.05

We also run the same analysis for the Donation Variety model (see Table 2.B3). Similar to the findings from Table 2.B2, we see that in Table 2.B3 the lag of Donation Variety, lag of Donation Amount, and the interaction between time since graduation and the instrumental variables are significant. Otherwise, we again see that the two instruments and their respective interactions with lag of donation amount are not significant in predicting Donation Variety. Again, this provides some empirical evidence that the instruments of Personal Marketing Budget and Impersonal Marketing Budget are good instruments for the Donation Variety model.

TABLE 2.B3: Instrumental variables regressed on donation variety

Variables (DV = Donation Variety)	**Selection Coeff. (Std. Err.)**	**Main Coeff. (Std. Err.)**
Intercept	-2.516 (0.056)*	0.660 (0.015)*
$\ln(\text{Variety}_{i,t-1})$	3.060 (0.030)*	0.624 (0.010)*
$\ln(\text{Gift}_{i,t-1})$	0.001 (0.00001)*	0.005 (0.001)*
$\ln(\text{PerMktgBudg}_{t})$	0.403 (0.397)$^{n/s}$	0.035 (0.036)$^{n/s}$
$\ln(\text{ImpMktgBudg}_{t})$	-0.370 (0.344)$^{n/s}$	0.048 (0.083)$^{n/s}$
$\text{TSG}_{i,t-1}$	0.231 (0.008)*	0.036 (0.002)*
$\ln(\text{PerMktgBudg}_{t}) * \ln(\text{Gift}_{i,t-1})$	0.00004 (0.00003)$^{n/s}$	0.000001 (0.000001)$^{n/s}$
$\ln(\text{ImpMktgBudg}_{t}) * \ln(\text{Gift}_{i,t-1})$	-0.00006 (0.00005)$^{n/s}$	0.000001 (0.000003)$^{n/s}$
$\ln(\text{PerMktgBudg}_{t}) * \text{TSG}_{i,t-1}$	0.058 (0.002)*	0.004 (0.0004)*
$\ln(\text{ImpMktgBudg}_{t}) * \text{TSG}_{i,t-1}$	0.057 (0.003)*	0.003 (0.0007)*
Model Fit		
Log Pseudolikelihood	-26,090.89	

* Significant at p-value < 0.01; ** Significant at p-value < 0.05; n/s Not significant at p-value < 0.05

APPENDIX 2.C: COMPARING DONATION VARIETY AND NUMBER OF INITIATIVES SUPPORTED

We estimate the same model as shown in the main paper with one exception. We substitute *Donation Variety* with (1) cross-donation (CD) to represent to the number of initiatives supported and (2) log of the cumulative donation amount (ln(Gift_Cum)) to represent the depth of gift amounts. The results appear in Table 2.C1.

TABLE 2.C1: Results for the donation variety and cross-donation models

	Depth and Breadth Model ($CD_{i,t-1}$ and $\ln(Gift\_Cum_{i,t-1})$)		**Donation Variety Model ($Variety_{i,t-1}$)**	
Variables	**Selection Coeff. (Std. Err.)**	**Main Coeff. (Std. Err.)**	**Selection Coeff. (Std. Err.)**	**Main Coeff. (Std. Err.)**
Intercept	0.302 (0.027)$^{n/s}$	2.157 (0.040)*	-0.032 (0.025)$^{n/s}$	2.412 (0.046)*
$\ln(Gift_{i,t-1})$	0.260 (0.004)*	0.087 (0.004)*	0.204 (0.003)*	0.252 (0.005)*
$Variety_{i,t-1}$	---	---	0.071 (0.021)*	0.157 (0.032)*
$CD_{i,t-1}$	0.030 (0.010)*	0.057 (0.015)*	---	---
$\ln(Gift\_Cum_{i,t-1})$	0.185 (0.005)*	0.331 (0.008)*	---	---
Extrinsic				
$ImpMktgCost_{it}$	0.024 (0.008)*	0.068 (0.15)*	0.044 (0.009)*	0.130 (0.020)*
$PerMktgCost_{it}$	0.002 (0.001)**	0.025 (0.005)*	0.006 (0.002)*	0.032 (0.007)*
$Econ_{t}$	2.075 (0.907)**	0.835 (0.267)*	1.524 (0.377)*	4.753 (0.503)*
Intrinsic				
$Degrees_{it}$	0.017 (0.004)*	0.081 (0.021)*	0.065 (0.013)*	0.087 (0.025)*
$Spouse_{i}$	0.088 (0.015)*	0.011 (0.022)*	0.093 (0.014)*	0.005 (0.027)$^{n/s}$
Interaction Effects				
$Variety_{i,t-1}$*$ImpMktgCost_{it}$	---	---	0.043 (0.004)*	0.003 (0.001)*
$Variety_{i,t-1}$*$PerMktgCost_{it}$	---	---	0.001 (0.0004)**	0.002 (0.0005)*
$Variety_{i,t-1}$*$Econ_{t}$	---	---	-4.143 (0.774)*	-0.606 (0.101)*
$CD_{i,t-1}$*$ImpMktgCost_{it}$	0.006 (0.002)*	0.002 (0.001)**	---	---
$CD_{i,t-1}$*$PerMktgCost_{it}$	0.0001 (0.00002)*	0.0001 (0.00001)*	---	---
$CD_{i,t-1}$*$Econ_{t}$	-1.323 (0.287)*	-0.244 (0.032)*	---	---
$\ln(Gift\_Cum_{i,t-1})$*$ImpMktgCost_{it}$	0.016 (0.001)*	0.007 (0.0009)*	---	---
$\ln(Gift\_Cum_{i,t-1})$*$PerMktgCost_{it}$	0.0002 (0.0001)**	0.0001 (0.00004)**	---	---
$\ln(Gift\_Cum_{i,t-1})$*$Econ_{t}$	-0.004 (0.001)*	-0.593 (0.238)**	---	---
Control Variables				
$Gender_{i}$	0.078 (0.014)*	0.360 (0.021)*	0.039 (0.013)*	0.439 (0.026)*
$Location_{i}$	0.035 (0.014)**	0.038 (0.012)*	0.054 (0.014)*	0.054 (0.025)**
Time Since $Graduation_{it}$	-0.038 (0.002)*	0.046 (0.003)*	-0.071 (0.002)*	0.033 (0.003)*
$AvgAGI_{it}$	0.0004 (0.0001)*	0.002 (0.0003)*	0.0002 (0.0001)**	0.003 (0.0003)*
$AvgGiving_{it}$	0.030 (0.014)**	0.565 (0.390)$^{n/s}$	0.064 (0.024)*	0.643 (0.259)**
Control Function Variables				
$ImpMktgError_{i,t}$	-0.069 (0.008)*	-0.108 (0.015)*	-0.058 (0.009)*	-0.146 (0.020)*
$PerMktgError_{i,t}$	0.004 (0.001)*	-0.022 (0.005)*	0.009 (0.002)*	-0.028 (0.007)*

* Significant at p-value < 0.01; ** Significant at p-value < 0.05; n/s Not significant at p-value < 0.05

The results of the model suggest that estimates for cross-donation (CD), log of the cumulative donation amount (ln(Gift_Cum)), and the interaction effects are all significant (just as the *Donation Variety* and interaction effects in the Proposed Model). This suggests that both sets of measures are capturing a similar effect (i.e. the key insights are the same). However, we do notice that the model fit (log pseudolikelihood) is better for the Donation Variety model.

It is also important to see which model is able to better predict the expected donation amount both in-sample and out-of-sample. To test the in-sample model fit differences, we compare the MAD and MAPE of the expected donation value for all donors in all time periods in the observation window. We find the in-sample MAD (MAPE) for the *Donation Variety* model is $60.11 (17.27%) and for the cross-donation and total donation model is $70.97 (18.38%). This suggests that the model with a single measure of *Donation Variety* captures more of the variation in expected donation amounts than the model with separate variables representing the breadth and depth of donations (cross-donation and total donation). Next, we test the out-of-sample fit of the model. To do this, we used the coefficients from the models to select the 'best' donors based on the predicted expected donation in FY 2013, given the original observation window of the data is to the end of FY 2012. We then see if the university foundation is better off selecting the top percentiles of donors (10%, 15%, and 25%) based on expected donation from the *Donation Variety* or cross-donation and total donation models (see Table 2.C2).

TABLE 2.C2: Donor selection using donation variety and cross-donation/total donation[a]

Percent of Donors Selected in FY2013	**Donation Variety**	**Cross-Donation (Breadth) and Total Donation (Depth)**
Top 10% of Donors	$94.9k	$88.9k
Top 15% of Donors	$104.2k	$98.1k
Top 25% of Donors	$115.9k	$110.0k

[a] Total values are all rescaled by the same constant at the request of the focal university foundation

We see from Table 2.C2 that, whether the foundation selects the top 10%, 15%, or 25% of donors based on the expected giving amount predicted by the two different models, that the model using *Donation Variety* helps the university foundation select donors with higher giving amounts in FY 2013 by 6.7%, 6.2%, and 5.4% respectively. All of these results suggest that using the proposed measure of *Donation Variety* is more valuable than the traditional (and separate) measures of breadth (cross-donation) and depth (total donation), as *Donation Variety* is a single measure (rather than two independent measures) that captures both the breadth and distribution of depth of donations made to a nonprofit organization.