The Causal Impact of Incentive Structure and Message Design on Product Diffusion: Evidence from Two Randomized Field Experiments

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Overview

59% of people consult friends for advice in making purchase decisions[1]. Not surprisingly, concomitant with the exploding growth of digital social networks, firms recognize the importance of using referral programs towards driving new business. Such schemes encourage existing customers with an incentive-laden call-to-action to engage their social networks by informing them about products and ultimately influencing and stimulating friends' purchase decisions. While referral marketing is a widely-adopted practice, the underlying science behind understanding and optimizing its various dimensions is nascent. The optimal design of referral program can be determined by three key design choices: incentive design (for both sender and recipients), call-to-action for information sharing (from the company to the sender) and message design (from the sender to the recipient). While previous research has examined the design of message sent from the senders to the recipients (Sun et al. 2014), no study has investigated how firms can optimally design the referral incentive and call-to-action message to engage customers. Given the increasing importance of online referral programs, it is crucial to close this gap.

Along with that, the massive growth in online social networking has revitalized academic interest in the power of social contagion as a force for individual and collective action. By conducting large-scale randomized field experiments (Aral and Walker 2011b, Bapna and Umyarov 2016), past studies causally identified peer effects in online social networks. Having established the causal existence of peer effects, it becomes natural to evolve towards asking how can we create, perhaps even maximize, social contagion by optimizing the various dimensions of the referral program. The broad goal of my

[1] Source: blog.talkable.com

dissertation is to study this issue. This dissertation examines two key design choices of a referral program. Specifically, it examines whether and how a firm can enhance the effectiveness of the referral program and increase social contagion by varying *incentives* shared by customers with their friends (Essay 1) as well as varying the *framing of the call-to-action messages* sent from the company to the customers (Essay 2).

The experimental design in both essays is motivated by the seminal research in economics that categorizes individuals into three categories based on their self and other regarding preferences (Andreoni and Miller 2002). Andreoni and Miller (2002) showed that individuals are either purely self-regarding, or they care about others, but not more than they care about themselves, or their preferences are substitutable between themselves and others. In line with this study, I designed the experiments to study which of the three key referral reward structures and three different framings of call-to-action maximize WOM-based adoption.

In the first essay, I focus on using *economic incentives* to maximize word-of-mouth as a mechanism for spreading awareness and adoption of a product. The broad category of economic incentives I use fall under the label of what are called referral rewards. A firm typically provides incentives to existing customers to bring in new customers. Such rewards can be monetary or cosmetic (e.g., status, badges) incentives to existing users for engaging in word-of-mouth, thereby increasing adoption of the product among their friends.

In practice, companies use different incentive structures when running a referral program. For example, some companies design incentive scheme so that the entire incentive can be given to the sender, whereas other design incentive scheme so that incentives can be split proportionally between the sender and the recipient, or can be rewarded entirely to a recipient as an altruistic gesture to encourage participation. However, although these schemes are being widely used in practice, their efficacy still remains an open question. Therefore, there is a need to understand which of these incentive structures is most effective in maximizing the diffusion of the product.

The experiment design involves manipulations of how the monetary reward is shared between the sender and the recipient of the referral: selfish reward (sender gets all or vast majority of the reward), equal reward (50-50 split), and generous reward (recipient gets all or vast majority of the reward). In the essay, I present evidence from two experiment studies that improve the understanding of different aspects of designing referral programs. Study 1's primary contribution is helping us understand these tradeoffs in the spread of offline word-of-mouth in a field based mobile social gaming context. Study 2 was designed to better understand the underlying mechanisms, as I was unable to track the users fully through the referral process in the first experiment.

Overall, the results of the two studies allow me to understand the tradeoff between incentivizing the sender and receiver in designing referral marketing programs. Study 1 points unambiguously towards the importance of a significant pro-social split in the incentives with a significant share for the recipient to increase offline word-of-mouth based diffusion. Study 2 takes place in a non-social context where I can observe the effect of treatments towards the sending rates of the referrals as well as record recipients' actions without the need for self-reporting. In study 2, I observe no significant difference across the incentive splits with regard to the overall number of new adopters. However, the results offer some interesting mechanism level insights into the inherent tradeoff between incentivizing the sender and the receiver. At the mechanism level, in contrast to ex ante expectations of rational utility maximizing agents, I find no significant difference in the three incentive schemes with respect to the rate of sending out referrals. This reveals that agents' utility is composed of both self-maximizing components and altruistic components in equal parts. The pro-social schemes, conditional on receiving a referral, have better conversion rates. This is confirmed by examining the recipient's decision to adopt the new game as a function of the sender's treatment group. The recipient's acceptance of the referral is highest in the generous scheme suggesting that firms can sacrifice some of the rewards to the sender without fear of cannibalization of the sender's actions. Together, the findings in the first essay suggest that a budget-constrained marketer should lean towards using referral incentive schemes that have a significant pro-social component in them in order to promote viral adoption in the digital world.

In the second essay, I study how firms can optimally design a call-to-action message to encourage existing customers to make online referrals, given a fixed incentive scheme. Past literatures on referral marketing show that what the receiver knows about the sender matters. For example, Sun et al. (2014) have found that simply adding information about the sender's purchase increases recipient's likelihood of purchase. However, no study has investigated how firms can optimally design the call-to-action to engage customers in initiating referrals in the first place. This essay is among the first to tackle the optimal design of the call-to-action question.

A close look at influential referral programs in the practice reveals that there are three types of call-to-action for sharing to the customer who may initiate referrals (i.e. 'sender'): a) the 'egoistic' call-to-action, where the firms highlight the reward to the sender, b) the 'equitable' call-to-action, where the firms highlight that both sender and her friends can get the reward, and c) the 'altruistic' call-to-action, where the firms highlight the reward to the friends. Among all three types of call-to-action for a referral, the 'altruistic' call is least observed, potentially driven by firms' perception that the sender may be more likely to initiate a referral if her own, ostensibly monetary, benefit is highlighted.

However, previous literature has shown that individuals may derive significant non-monetary payoff from helping others in the form of either warm glow or pure altruism. Thus, the altruistic call may enhance customers' pure altruism or warm glow therefore encourage more sharing from them. In addition, the altruistic call may reduce customers' psychological cost of feeling guilty about gaining referral rewards (Rue and Feick 2007). Given above considerations, I posit, and causally demonstrate, via a large scale randomized field experiment involving 100,000 customers, that altruism plays a key role in activating the ideal form of product advocacy from those initiating referrals. When contrasted with egoistic and equitable framing of calls-to-action, the altruistic framing yields a significantly higher propensity to initiate a referral as well as a significantly higher number of successful referrals. The effects are economically significant - altruistic framing yields 99% and 30% higher total number of referrals than egoistic framing and equitable framing respectively, the latter two being statistically indistinguishable from the control group. Further, altruistic framing yields 425% and 135% levels of recipients' purchases compared to egoistic framing and equitable framing respectively. The yields associated with egoistic and equitable framing are again statistically indistinguishable from the control group. Additional mechanism level analysis that interacts the treatments with customer characteristics such as repeat purchase, net promoter score, and time since last purchase, and a post-experiment survey, confirm my hypotheses about the importance of an altruistic element in generating a higher quality of advocacy and reducing referral frictions. The altruistic group, positively interacts with customer affinity variables such as repeat purchases indicator, net promoter score and positively interacts with the recency of purchase. Further, subjects in the altruistic group report lower levels of guilt associated with sending a referral and are more readily able to identify friends and family who might benefit from the product. Together, this results in higher quality of advocacy which explains the robust (to multiple econometric specifications) findings on the benefits of altruistic call-to-action for online referrals.

This dissertation offers several contributions to several streams of prior research. First, the study enriches the literature on digital word-of-mouth by identifying the causal effect of incentive structure and call-to-action design – two key elements in designing referral programs. Although, designing key elements of an online referral program to drives social contagion has been of much interest to both academics and practitioners, identifying the causal effects of different design are methodologically hard because of endogeneity (Manski 1993). Using a large scale randomized experiment, I show that pro-social incentive structure and altruistic framing work best in driving referrals and related outcomes. Second, this essay also closes the gap of identifying the optimal design of online referral program. Existing studies of designing referral programs on WOM mainly focused on senders' behavior and rarely considered incentive sharing schemes or different message design. I contribute to the literature by studying how firms can optimally design the incentive and message to the sender (call-to-action) to engage customers. Finally, my study is also among the first to show that altruism is an important driver of information sharing among customers and how such motive leads to sharing decision and sharing outcomes. Specifically, the study provides concrete and causal support to the hitherto under-studied role of altruism in creating word-of-mouth. In the IS literature, a few studies have analyzed motives of online behaviors such as community participation and found that they are likely to be driven by altruism (Bitzer et al. 2007, Anderson and Agarwal 2011, Jabr et al. 2014, Xia, Huang, Duan, and Whinston 2012). However, despite the large volume of online referrals, little is understood about its underlying motives, as well as how companies can leverage such motives. This dissertation, taking advantage of a randomized field experiment, and including a detailed analysis over multiple moderators and a large-scale survey, presents strong and consistent evidence that altruism is crucial in driving referrals. This work also provides clear guidance on how firms can leverage altruism to improve referral behavior and outcomes.

As firms heavily rely on referral marketing, understanding how incentive structure and call-to-action messages causally impacts the diffusion of products through WOM is a crucial step in developing referral program strategies for increasing adoption of products.

I believe this dissertation enriches the literature by providing empirical analysis of different referral reward schemes and messages, as well as provide great implications to companies seeking to maximize returns from information sharing by providing information about the optimal design choices.

Essay 1: Examining the Impact of Incentive Structure on Referral Program Design

1. Introduction

The massive growth in online social networking has revitalized academic interest in the power of social contagion as a force for individual and collective action. Of particular interest is the recent move towards large-scale in-vivo randomized field experiments to causally identify peer effects (Aral and Walker 2011B, Bapna and Umyarov 2016) in online social networks, a significant scientific challenge with purely observational data. This new wave of literature gives us confidence that peer-effects are 'at-work' in the general population of users in online social networks. Having established the causal existence of peer effects, it becomes natural to evolve towards asking how can I create, perhaps even maximize, social contagion using specific mechanisms that may be at work in creating social contagion. This is the focus of the first essay. In particular, I focus on using economic incentives to maximize referral based awareness and adoption of a product. Note that while peer influence works through a variety of mechanisms such as imitation, status seeking, creating awareness, explicit or tacit persuasion, observational or social learning (Aral 2011), I focus on friends inviting friends through word-of-mouth because it is an important, possibly dominant[2], social contagion mechanism. In terms of offline word-of-mouth, it has the additional challenge that it has traditionally been hard to

[2] For instance, industry reports suggest that face to face invites have 5x the acceptance rate of Facebook invites as per http://www.nielsen.com/us/en/newswire/2009/global-advertising-consumers-trust-real-friends-and-virtual-strangers-the-most.html

measure, as it does not lend itself to digitization. I will detail how I overcome this challenge when I present the institutional context in this essay.

The broad category of economic incentives I use fall under the label of what are called referral rewards. A firm typically invites an existing customer to refer and bring in another customer and offers a reward to the existing customer. Such rewards can be monetary or cosmetic (e.g., status, badges) incentives to existing users for engaging in word-of-mouth, thereby increasing adoption of the product among their friends. For instance, Dropbox provides extra 500MB of space to the user per referral once a user refers new customers[3]. Groupon also offers a user $10 Groupon Bucks[4], which can be used toward any purchase on the website, when a user refers a new customer and that new user makes a first purchase of $10 or more within certain number of hours. On the other hand, companies like Lyft, which facilitates peer-to-peer ridesharing by connecting passengers to drivers using a mobile-phone application, have tried referral schemes in which both a new customer and her referrer got $5 each[5]. In contrast, Blue Apron, an online meal subscription service, has a different referral reward strategy that allows its existing users to send a free box of gourmet food to a friend, who is not yet a user of the service[6]. But although these schemes are being widely used in practice, their efficacy still remains an open question. Scott Cook, CEO of Intuit, while speaking on their ad-hoc approach to designing referral reward schemes said:

[3] https://www.dropbox.com/referrals
[4] http://www.groupon.com/referral
[5] https://www.lyft.com/help/article/1455280
[6] https://awesomesauceeats.wordpress.com/tag/blue-apron/

"…We've tried various artificial stimulants to word of mouth, like financial incentives to recommenders. None have worked. Some produced isolated, but surprising, negative reaction: 'I don't sell my friends for a bit of cash'[7]…"

This begs the design of a systematic study of effectiveness of these different incentive schemes on spreading word-of-mouth. Therefore, in this essay, I explore this research question using a two study design that sheds light on different aspects of offline and online word-of-mouth. In Study 1, I deploy a field experiment set in the context of a mobile social gaming application, where the goal of the participants is to spread the adoption of the mobile gaming app. The context of social gaming is important and interesting especially given the growth of a new digital economy that is built around enabling users to have a shared experience. Study 2 was designed to better understand the underlying mechanisms, as I am unable to track the users fully through the referral process in the mobile environment. It is a more controlled experiment with student subjects where the goal is to spread the adoption of a web-based word game and the entire referral process takes place via my custom online platform that allows for extensive tracking of the actions of senders and receivers of the referral incentives.

The research design involves manipulations of how the monetary reward is shared between the sender and the recipient of the referral. In particular, I aim to investigate the tradeoffs between incentivizing the sender of the referral and the recipient of the referral. It is obvious to state that successful referrals are contingent on positive actions from both

[7] Rosen 2009, The Anatomy of Buzz Revisited: Real-life lessons in Word-of-Mouth Marketing, Crown Business.

the sender and the receiver. The research design is motivated by multiple theories from economics and sociology. The initial motivation of the study comes from seminal research in economics that categorizes individuals into three categories based on their self and other regarding preferences (Andreoni and Miller 2002). In the study, the authors showed that individuals are either purely self-regarding, or they care about others but not more than they care about themselves, or their preferences are substitutable between themselves and others. In line with this finding of Andreoni and Miller (2002), I test three different incentive schemes: a) the ‘selfish’ reward scheme, where the sender gets the reward, b) the ‘split’ reward scheme, where the sender and the recipient split the reward equally, and c) the ‘generous’ reward scheme, where the entire reward is given to the recipient. The research question asks which of these reward schemes is the most effective in stimulating social contagion through WOM-based adoption.

Unfortunately, there is no clear consensus emerging from the prior literature regarding this question. Rational choice theory dictates that referral rewards to sender will motivate them to invite others, while equity theory encourages an even split in the reward between the sender and the recipient in order to address their sense of equity and fairness. More recent work from Dunn and Norton (2013), however, argues that individuals are happier when they can be pro-social by acting generously, which motivates rewarding the recipient only.

Evaluating such effects of different referral reward schemes on WOM have been difficult so far because peer effects and WOM are typically endogenous (Manski 1993, Van den Bulte and Iyengar 2011) and especially for offline WOM, the effects are difficult to trace or measure. But online and mobile environments of today give richer data and attribution ability that can potentially be useful to overcome the measurement problem. Additionally, the design of the randomized experiment with different reward structure allows for causal interpretation of the treatment effects (Aral 2011). The use of a randomized field experiment is to overcome myriad sources of endogeneity that would plague pseudo-treatment effects from observational data based studies of effectiveness of referral incentive schemes. Depending on how companies run the different incentive schemes, these include, but are not limited to a) potential omitted variable bias stemming from unobserved consumer characteristics that could be correlated to different treatment types and outcomes, b) selection bias if companies were targeting certain types of users with certain schemes, and c) reverse causality even if more active referring was linked with higher rewards.

This essay complements two streams of prior research on IS and marketing: estimating causal peer influence in networks, and constructing referral incentive schemes to promote WOM based adoption. While there have been recent studies estimating causal peer influence in networks (Aral and Walker 2011B, Bapna and Umyarov 2016), as well as analytical and experimental studies in optimal referral literature and WOM (Kornish and Li 2010, Wirtz and Chew 2002, Ryu and Feick 2007), there has been relatively less work on how to use viral incentives to create contagion.

The main finding from the two experimental studies in this essay suggest that a budget-constrained marketer should lean towards using referral incentive schemes that have a significant pro-social component in them in order to promote viral adoption in the digital world. The key result from Study 1 that the generous treatment maximizes induced adoptions adds to the body of evidence against the purely rational theories of self-maximizing economic agents. Study 2 helps us understand some of the underlying mechanisms. One of the interesting results emerges from examining the effect of treatments on the senders' decision to initiate referrals. The fact that this does not significantly decay as more money is taken away from the sender and given to the recipient reveals that the sender's utility is made up, equally, of a self-interested component and an altruistic component.

It is important to note that the context matters. There are important differences in the overall results from the two studies that have related but different context. I would be cautious in generalizing the claims beyond the two particular context and call for additional future research using designs similar to the one proposed in this study. Specifically, future research should cull out the linkage between the three incentive schemes and the underlying motives behind the senders' and recipient's actions in the context of referral marketing.

2. Literature Review

2.1 Social Contagion

Causal identification of how peer effects drive social contagion in the general population of users in online social networks has been of much interest to both academics and practitioners. But identifying social contagion effects are methodologically hard because user characteristics and behavior tend to cluster in online social network (Aral and

Walker 2011b). However, randomization is an effective method for identifying social effects from homophily mechanisms and other confounders, and can help in clearly estimating causal peer influence in networks. Recent research efforts have therefore focused on overcoming the challenges of analyzing purely observational data by using large-scale in-vivo randomized field experiments to causally identify the presence of peer effects (Aral and Walker 2011b, Bapna and Umyarov 2016) in online social networks. Aral and Walker (2011a) focus on studying the effectiveness of different viral product design features in creating peer influence and social contagion in new product diffusion by conducting a randomized block design field experiment on users of Facebook. Bapna and Umyarov (2016) conduct a randomized field experiment in the context of a freemium social network to find the causal relationship of peer effect on premium subscriptions. They distribute a premium subscription gift to randomly selected users, which work as an exogenous random assignment of a treatment to a subset of the population, and observe whether being connected to the users that received the premium service increases the likelihood of acquiring this service.

Although these previous works have established the causal existence of peer effects, empirical evidence of what mechanisms drive behavioral contagions in social networks and how we can promote such contagion is still somewhat lacking (Sundararajan et al. 2013). Aral (2011) suggested that social contagion may be driven by a combination of different kinds of possible mechanisms such as awareness raising, explicit or tacit persuasion, observational or social learning or imitation among others. Another important, and possibly dominant, mode of social contagion mechanism is the word-of-mouth (WOM). Individuals can exercise peer effect by sharing their overall experience and satisfaction level of the product. This WOM can change peers' understanding of the product as well as peers' expectations of utility function in two ways. Peers might change their behavior because they become aware of the existence of the product or be persuaded of the benefits of the product they already know (Aral 2011). However, traditionally it has been hard to measure offline WOM as it does not lend itself well to digitization. Study 1 of this paper adds to the literature on social contagion by focusing on *offline word-of-mouth* as a mechanism for spreading awareness about a new product, and exploring how it can be stimulated by the design of economic incentives.

2.2 WOM and Incentive Design

Several studies have recognized the importance of carefully managing referral programs to stimulate word-of-mouth. Biyalogorsky et al. (2001) develop an analytical model in which a customer's delight level with the product causes referrals, and identified conditions under which referral reward is more effective than price reduction in enhancing a firm's profitability. Based on the idea of social motives, Kornish and Li (2010) establish a compensatory model in which senders explicitly care about their friends' satisfaction with their recommendations rather than their own delight with the product. Wirtz and Chew (2002) and Ryu and Feick (2007) investigate the effectiveness of referral bonuses in experimental settings. Wirtz and Chew (2002) examine the role of incentive, deal proneness, satisfaction, and tie strength on WOM. Ryu and Feick (2007) study the relationship between referral rewards and tie strength. They find that rewards are particularly effective in increasing referral, especially for weak ties and weaker brands. Although these studies examine the effect of referral incentive design on WOM, a key limitation has been that these were conducted purely in a lab environment. To the best of my knowledge, this work is the first study that combines insights from a field and lab experiment on the impact of incentive design on the adoption of a digital good. This complements prior work by analyzing the behaviors of real users in reaction to various referral incentive schemes using a randomized field experiment.

2.3 User Behaviors and Incentive Design

The incentive structure of customer referral programs determines how the reward is divided between the sender who makes a referral and a recipient (new customer) who accepts it. Recent studies from behavioral economists suggest that this division of incentive can greatly influence the outcome of the referral program because senders exhibit three types of behavior: generosity, equity seeking, or selfishness. In an experiment setting, Andreoni and Miller (2002) show that while only quarter of subjects reveal selfish behavior, the rest of subjects exhibit a significant degree of rationally altruistic behavior. Moreover, they demonstrate that almost half of the participants' behavior was consistent with one of the 3 CES utility functions: perfectly selfish, perfect substitutes, or Leontief. Those with Leontief preferences always divided the surplus equally while those with perfect substitute preferences either act generously or selfishly depending on the price of giving. This observation provides the theoretical foundation for my experiment design in which I have explored these three reward-referral mechanisms: selfish reward (sender gets the whole reward), equal reward (the reward is split equally between the sender and recipient), and generous reward (recipient gets the whole reward).

However, there is no clear consensus emerging from the prior literature regarding which of these incentives schemes would maximize adoption of the product through referrals. Dunn and Norton's research on pro-social happiness effect dictates that people are happier when they spend money on others (Dunn and Norton 2013), which implies that referral reward programs may benefit from tapping into the pro-social, "generous", guilt-free incentive condition by giving the entire reward to the recipient. Equity theory says that individuals seek equity and fairness in what they give and receive from others (Walster et al. 1973), which suggests that a split condition that gives "equal" rewards to the sender and recipient may be an effective referral mechanism. Lastly, rational choice theory denotes that the reward should be given to a sender in order to kick-start this referral process. That is, by tapping into the "selfish", reward-seeking behavior of users, marketers can mobilize them to refer and recruit more friends to adopt the product. Aherns et al. (2013) conduct a field experiment in an online shopping mall with e-referrals and find that inequity between the sender and recipient's reward amount favors the sender to enhance WOM.

On the other hand, some theories predict that providing incentive can prevent referrals. For example, metaperception theory denotes that giving incentive can prevent referrals when the incentive for referral is rewarded only to the sender. Metaperception refers to the process by which people decide based on what others may think of them or their behaviors (Laing et al. 1966). According to metaperception theory, in a non-incentivized WOM setting, senders will perceive themselves as performing a good action and believe that the recipients too would judge it that way. However, in an incentivized referral situation in which a referral is rewarded only to the sender, a sender may think that the recipient will perceive this referral as being driven by a desire to get the reward rather than an intrinsic motivation of inviting a friend (Wirtz et al. 2012). In this case the probability of referral will likely decrease.

It is difficult to reconcile all these differing viewpoints regarding the efficacy of the different incentive schemes in the absence of a robust randomized experimental design. In this essay, I conduct a randomized field experiment to address this issue, namely, how to structure such incentives (i.e., divide it between the sender and the recipient) to increase adoption of digital goods, in this case – a mobile social game app in study 1 and a non-social online word game in Study 2, through referrals. This essay enriches the literature on viral incentive design by providing empirical analysis of these different referral reward schemes, and presents a first step in the effort towards deriving greater consensus on this topic.

3. Field Experiment Based Study 1

3.1 Institutional Details: Mobile Social Games

For Study 1, I partnered with a company that specializes in developing social gaming applications to compare the effectiveness of the three referral reward structures in stimulating adoption of their new game through offline WOM. This company is of particular interest because its products are digital versions of popular board games, which therefore feature two important directions in which the digital goods have been evolving – mobile and social. The widespread adoption of mobile devices like smartphones and tablets has led to a burgeoning market for mobile applications, in particular, gaming applications like the one used in this experiment. Popular multiplayer social gaming applications similar to the app used in this study include Draw Something, Words With Friends, Heads Up, and Evil Apples.

The mobile gaming market is one of the fastest growing segments in today's digital market. In 2013, out of the $75.5B gaming industry, mobile phone gaming accounted for $17.6 B with about 1.11 B gamers. By 2017, the mobile gaming market is expected to reach $35.4 B in revenues and attain 34% share of the gaming market[8]. The aspect of social interactions embedded in the design of these games is also a reason for their growing popularity. These games are even becoming a fun-filled way of providing training, teaching social skills, encouraging collaboration, and devising strategy. As the mobile gaming market continues to grow, the particular context of this study itself becomes an important market to investigate the question of how to structure the referral rewards to generate adoption of games through WOM.

The mobile game developing company I partnered with has created a social game that is intended to be a party game, one that is played in a communal environment[9]. So all the players have to be co-located when they play the game. The application is a multi-player game in which each player takes turn to ask funny questions from a pack of content cards and other players get to choose answers from a set of preloaded options, and earn points for best answers. Sample screenshots from the game are shown in Figure 1. In addition to content cards, the game also has a number of cosmetic features to enhance interaction among players (e.g., screen avatars, like and dislike options). The

[8] http://www.newzoo.com/insights/global-games-market-will-reach-102-9-billion-2017-2/
[9] This social app needs at least three co-located players to play a round of the game.

game was released on both Android and iOS app stores for free. The company monetizes through in-app purchase of additional packs of content cards and various cosmetic features.

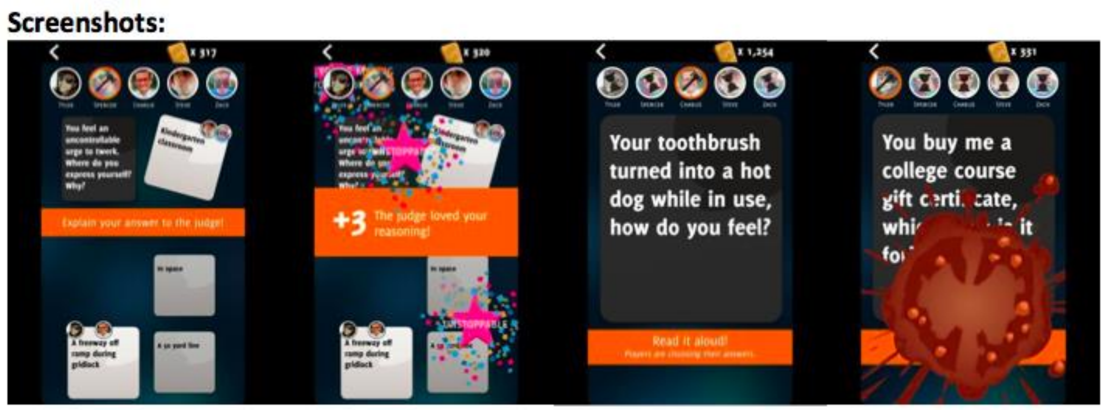

Figure 1: Screenshots of the Mobile Game App

Because the game can only be played among co-located players, users who discover and directly download the game from the app store (i.e., organic users) have to invite their friends to play the game with. Therefore, offline WOM, such as, face-to-face invitations to join the game is a key mechanism that drives the adoption of this product. The app uses a geo-sensing feature to add co-located players[10] to the game and to help new players explicitly identify their senders. The screen to attribute an invitation pops up at the beginning of the first game played by a user if this user's account was created within the last hour and this user has never played the game before. The invitation attribution screen is dynamically populated with a list of co-located users with whom this new user can play the first game and from which he/she can select the sender.

[10] As far as the geo-sensing feature is concerned, co-located users can be within 1 degree of latitude and longitude of each other. But only users that are actually physically co-located can play this game together because it requires verbal interaction.

Conversely, a user is classified as an organic user (i.e., who likely discovered the app on their own), and hence, do not see the invite attribution screen, if they do not play their first game within an hour of downloading the app [11]. The reason - based on the conversations with the CEO of the gaming company - is that it is unlikely that an organic user will manage to find or convince at least two other users to download, install, sign up, and play the first game all within an hour[12].

3.2. Study 1 - Experimental Design

The experimental design of this essay is motivated by the work of Andreoni and Miller (2002) which categorizes individuals into three categories based on their self and other regarding preferences. They showed that individuals are either purely self-regarding, or they care about others, but not more than they care about themselves, or their preferences are substitutable between themselves and others. Therefore, I designed the randomized field experiment to study which of the three key referral reward structures, namely, selfish (sender gets the entire incentive), equal sharing (incentive is equally divided), and pro-social (recipient gets the entire incentive), maximizes WOM-based adoption.

Since I partnered with the mobile social gaming company before the release of this app, I was able to record data about two types of users in the trial – "existing users,"

[11] A potential misclassification of an invited user as an organic user may happen in the unlikely event where the invited user is instructed to download the app in advance in anticipation of playing the game later on. If the duration between the app download and the first game is more than an hour, then this user will not see the invitation attribution screen. However, because of randomization, there is little reason for this scenario to arise systematically in any treatment group, and as such is not a major threat to our inference. Additionally, this is not relevant in Study 2, as all invitations and attributions are digitally tracked.

[12] However, even if this scenario were to arise, it would result in an organic user attributing his/her invitation to a new player and vice-versa. If such invitation attribution cycles occur, these data points are excluded from the analysis. Moreover, there is little reason for this scenario to arise systematically in any treatment group. Additionally, this scenario is not able to arise in Study 2.

defined as those who downloaded the app since its release and updated[13] it at the beginning of the experiment (treatment) period, and "new users" who joined during the experiment period. Because the app was newly released and had no prior brand history, the distinction between the new and existing users is likely based on their time of discovery of the app rather than any intrinsic difference between them. But even if these users have any intrinsic differences, randomization in the assignment of the users across the different treatment groups allows me to identify and compare the outcomes of the different incentive schemes (treatments). The duration of the pre-treatment and experimental (treatment) phases are reported in Table 1.

Trial Phases	**Months (in 2014)**
Pre-Treatment Period	March 22 – April 21
Experiment (Treatment) Period	April 22 – June 2

Table 1. Trial Phases of the Experiment

Group	**Control Group (No reward, no reminders)**	**(Test Group 0) T0: No reward, but reminders**	**(Test Group 1) T1: Selfish reward**	**(Test Group 2) T2: Equal reward**	**(Test Group 3) T3: Generous reward**
Assignment Probability	**0.12**	**0.22**	**0.22**	**0.22**	**0.22**

Table 2. Assignment Probability of Experiment Groups

Users of the mobile application joined the trial either by discovering it organically while browsing the app stores (i.e., organic users) or by being invited by existing players. When a user joins the trial, she is randomly assigned to one of the five groups of the experiment according to the probabilities displayed in Table 2. Three of these groups

[13] The app update was automatic for any existing user when they opened the app after the beginning of the experiment period. Users who never updated their app, *i.e.*, who had stopped playing prior to the experiment period, were excluded from the trial.

were test groups defined by their referral reward structure – selfish (sender gets the entire incentive), equal split (incentive is equally divided), and pro-social (recipient gets the entire incentive)[14]. Users in all these groups got reminder notifications to invite their friends to play with, and to get rewarded according to the incentive structure on offer for that user's group. A fourth treatment group (T0) had no referral rewards but provided users with the reminder notifications to invite new friends. Comparing the previous treatment groups with the fourth group allows me to see (in Section 3.3) that although customer pull-back mechanisms, such reminder notifications, are popular mechanism for promoting adoptions, the right incentive schemes can have a significant impact in accelerating adoption. The other is a control group – a group with no reward and no notification. This control group provides the benchmark for the diffusion rate of natural invites. Because social games require co-location of players, a user may already have some incentive to recruit other people to play the game with. This intrinsic motivation, if present in the population, will show up in this control group and anything I observe in the data from the treatment groups will be driven by what is over and above unobserved factors and caused by the randomized treatment. In Appendix Table 22 I show that there is no significant difference across the control and treatment population of existing users at the beginning of the experiment phase.

Next I discuss how the users join the experiment phase of the trial. The experiment design randomly allocates users into test groups according to assignment probabilities in Table 2, and the experiment duration is the same for each group. The

[14] While a continuous range of incentive splits of the form (x, 100 – x) between sender and recipient are possible, I chose (100, 0), (50, 50), and (0, 100) as the treatment options because these can be unambiguously interpreted as purely selfish, equal split, and purely generous.

treatment assignment is constant for a given user for the entire duration of the experiment. When a player enters the experiment by downloading or updating the app (for existing users), she immediately enters a one-week period, called the incentivized period, during which the player can earn the referral reward for inviting new users. As discussed previously in Section 3, a new user can identify who her sender was and the reward received (if any) by the sender and recipient is based on the group that the sender belongs to, provided that the sender is still in the incentivized period. When a recipient attributes the invitation to a sender, the incentivized period for that sender resets. However if a recipient attributes an invitation to an sender when the sender is no longer in her incentivized period, then no reward is given out for that particular invitation but the incentivized period of the sender resets. Further invite attributions by new recipients will allow the sender to continue remain in an active incentivized period. Even though it does not empirically appear to be the case, it is arguably possible that the resetting of incentivized period for those who successfully invited someone within a week may potentially result in endogenous treatment durations. Therefore, I examine the sensitivity of the main results to this issue by restricting the sample to the first seven days in the experiment phase for all the users when they are equal in terms of being in incentivized treatment period and randomly assigned.

In summary, based on the experiment design, when a user updates or downloads the app during the experiment period, regardless of whether she is an existing user or a new user, she will be randomly assigned to one of the groups and be a subject of the experiment. For each group, there are a similar number of existing users and new users who were the part of the experiment for a similar period of time[15]. The referral incentives I offered during the trial were 1000 virtual coins that can be redeemed at any time in the app to purchase additional content and cosmetic game items[16]. That is, a sender in a selfish reward group will get all the 1000 coins and recipient gets nothing, in an equal reward group both the sender and recipient get 500 coins each, and an sender in the generous reward group gets nothing but the recipient gets all the 1000 coins. Here, 1000 virtual coins are equivalent to $1 in worth, a value that compares well with the average price of such online apps. It bears mention that I do not consider the case where both sender and recipient get 1000 coins each because it is akin to "growing the size of the pie" instead of dividing it. A profit-seeking game developer is interested in only awarding a certain amount of virtual coins per referral (*e.g.*, 1000 coins in this case) and the question is how to split it in a way that improves referral-based adoption of the game.

As mentioned earlier, the mobile application also gave reminder notifications[17] to the players in the four treatment groups during their incentivized period about the rewards they can receive upon inviting new people to adopt the game. Fig. 2 shows the

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[15] Since players join the experiment at the different time point during the experiment period, the panel is imbalanced at an individual level but balanced at the group level because of random assignment. I later show this using a variable 'join_time_duration'.

[16] These game items are question cards, user avatars, virtual weapons, etc. As these items are tied to the purchasing user and provide them with features that others don't have, they largely have an individual value. But arguably, in a social setting these items can also increase engagement of other players within a round of the game. In Table 20 of Appendix A, I therefore provide results with the number of other players included as a control. Additionally, Study 2 does not have such issues, as the reward is entirely monetary.

[17] The app provided two types of reminders – one is a local notification that is sent out the first time 3 hours after the app's download (to nudge them to invite friends) and then onwards on every Friday (to encourage them to play the party game in the upcoming weekend), the other is an in-app notification that is visible in the home screen once the app is launched. These reminder mechanisms were consistent across all treatments. The difference in results I find across the treatment groups is therefore driven by the incentive schemes.

screenshots for the reminders sent to the different groups of the trial to encourage offline WOM based invitations to their friends.

Upon successful referrals, the senders and recipients also received messages informing them about the rewards they received. These sample messages are shown in Fig. 3. It is worth noting here that for the selfish reward group the app only informs the sender about the reward and does not reveal to the recipient that the sender was rewarded for the referral. This was done to reduce the potential negative impact that guilt may otherwise have in a social setting in the case of users assigned to the selfish reward group.

No reward group	Selfish reward group	Equal reward group	Generous reward group
Thank you for joining Hearsay! This game is best played with new friends. Invite someone today! Okay	Thank you for joining Hearsay! Invite a new friend to play before the next weekend is over and we will reward you with 1,000 coins! Okay	Thank you for joining Hearsay! Invite a new friend to play before the next weekend is over and we will reward both of you with 500 coins each! Okay	Thank you for joining Hearsay! Invite a new friend before the next weekend is over and we will reward them 1,000 coins on your behalf! Okay

Figure 2. Sample Reminder Notifications of Different Treatment Groups

No Reward Group	Selfish Reward Group	Equal Reward Group	Generous Reward Group
Message seen by Invitee upon adoption			
N/A	N/A	Thanks for joining Hearsay! You and the friend who invited you both earned 500 coins! Okay	Thanks for joining Hearsay! You just earned 1,000 coins thanks to the friend who invited you! Okay
Message seen by Inviter upon successful referral			
Thank you for inviting a friend to join Hearsay! You're awesome! Okay	Thank you for inviting a friend to join Hearsay! Here are 1,000 coins just for you! Okay	Thank you for inviting a friend to join Hearsay! You both earned 500 coins for spreading the love! Okay	Thank you for inviting a friend to join Hearsay! Your friend just earned 1,000 extra coins thanks to you! Okay

Figure 3. Sample Messages upon Successful Referrals

3.3 Study 1- Analyses and Results

3.3.1 Data and Descriptive Statistics

The summary of the various groups and the referral reward mechanism for each group is listed in Table 3. In the trial period, there were 2092 players in total who adopted the app, out of which about 1664 were organic adopters (non-invited users who discovered the app on their own).

Testgroup	Referral Reward mechanism	Sender Incentive (%)	Recipient Incentive (%)	Organic Users
Control Group	No rewards, no reminders	0	0	181
Treatment Group (T0) – No reward, but reminders	No rewards, reminder notifications	0	0	371
Treatment Group (T1) – Selfish reward	Sender gets 1000 virtual coins	100	0	355
Treatment Group (T2) – Equal reward	Sender and Recipient both get 500 virtual coins each	50	50	373
Treatment Group (T3) – Generous reward	Recipient gets 1000 virtual coins	0	100	384

Table 3. Summary of Experiment Groups and Incentive Schemes

For each user, I know the time they joined the site, whether they joined the site before the experiment phase (*existinguser* = 1 for existing users, 0 for new users), and whether they joined the site on their own (*invited* = 1 when the user was invited, 0 when the user joined on her own). I define a variable, *join_time_duration*, measured as the number of days between the date when the user joined the trial and the end date of the trial (June 2), and a variable, *app_update_date*, measured as the number of days elapsed between the start date of the treatment phase of the trial (April 21) and the day when the user actually joined the treatment by updating (for existing users) or downloading their app (for new users).

In addition, I collect login and gaming activities for the users in the sample for the pre-treatment and treatment period regarding which group of players play together, the frequency and duration of games played by each group, the location at which the games are usually played, etc. For robustness purposes, such as establishing the equivalence of the treatment groups and control group, I constructed the following social engagement metrics: *login_days* (number of days that a user logged in), *login_hours* (number of hours that a user logged in), *game_count* (number of games that a user played), *game_total_player* (number of total players that a user played with), *game_ave_player* (average number of players a user played with), *game_total_time* (number of total seconds a user played a game), *game_ave_time* (average seconds of games a user played), and *location_count* (number of unique locations a user played at).

3.3.2 Pre-treatment Balance

I first analyze the data gathered in the pre-treatment period about the behavior of the players assigned to the control and experimental groups to check if there are any statistically significant characteristic differences between these groups. The summary statistics and comparisons of the pre-treatment behavior across users in the different treatment and control groups are given in Appendix Table 22. I find the treatment and control groups have statistically indistinguishable properties, evidenced by a lack of a directional pattern in the magnitude as well as a lack of significance, prior to manipulation. This is expected given random assignment, but it is standard protocol in the *in-vivo* field experiment literature to establish this (Bapna and Umyarov 2016).

3.3.3 Effects of Incentive Structure on the Number of Induced Adoptions

In the analysis, I focus the study on the behavior of the 1664 organic adopters (i.e., those who discovered the mobile game application from the app store[18]) across the different treatment and control groups because these individuals are completely free of any priming effects of generosity or selfishness that will be present among subsequent senders[19].

I begin the analysis by exploring changes in the number of adoptions (e.g. successful invites) that were induced by the treatment over the incentivized period. Given randomization, I can analyze the aggregate effect of the treatment using t-tests. Table 4 indicates that only the generous group beat control in the *Adoption_count*. The generous group outperforms T0, the no reward but reminders group at the alpha=0.1 level.

Testgroup	Mean	SE	Std Dev	Min	Max	t-value (Treatment vs. Control)	Pr >t
Control	0.0216	0.0132	0.1793	0	2		
T0: No reward, but reminders	0.0318	0.0118	0.2284	0	2	0.58	0.5637
T1: Selfish reward	0.0386	0.0155	0.2948	0	3	0.83	0.4048
T2: Equal reward	0.0521	0.0159	0.3106	0	3	1.48	0.1401
T3: Generous reward	0.0662	0.0181	0.3581	0	3	1.99	0.0469

Table 4 : The mean comparison of the number of adoptions across groups

[18] I would like to note that the study focuses on encouraging WOM from the population organic users, who likely have a pre-disposition to engage with the app in context. In practice, marketers too care about designing referral reward programs directed at early adopters to help reach a critical mass of users.

[19] In other words, those players who were themselves invited by organic users may be primed differently depending on what referral reward they received (if any) at the time of invite attribution. Studying the effect of priming on subsequent behavior of non-organic adopters would be an interesting extension. Unfortunately, this present data set does not have enough power to obtain statistically significant results on this issue.

Given that the outcome variable *Adoption_count* is a count variable, I also verify the result from Table 4 using a Poisson regression (Table 5) using treatment as an independent variable uncorrelated with the residual. As demonstrated in Tables 4 and 5, only the average effect of generous treatment on new invites is significant.

Parameter	**Estimate**	**Standard Error**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-3.8122	0.5000	-4.7922	-2.8322	58.13	<.0001
T0: No reward, but reminders	0.0952	0.1443	-0.1877	0.3781	0.44	0.5094
T1: Selfish reward	0.5791	0.5669	-0.5321	1.6903	1.04	0.3070
T2: Equal reward	0.4432	0.2739	-0.0936	0.9799	2.62	0.1056
T3: Generous reward	0.3732	0.1790	0.0223	0.7241	4.35	0.0371

Table 5 : Result of Poisson model

These results indicate that the test groups with no reward but only notification, the selfish referral reward (i.e., sender gets the whole reward) and the equal split reward (i.e., fair division) do not perform much better than the control group. However, the players in the generous group promote a significantly higher number of adoptions than the players in the control group. This provides initial evidence that, in the context of mobile social games, reward schemes with a pro-social component tend to dominate the egocentric referral schemes. Because the outcome measure is self-reported, it could be the case that the generous scheme may be linked with higher propensity amongst recipients to report, and conversely a lower propensity to report if there is nothing in it for the recipients. I argue that such a behavior is not without a significant social cost, which is substantial in a physical co-located setting, of denying someone you are going to socially interact with a fairly obtained monetary reward. Further, I deal with this potential bias by virtue of replicating the treatment design in Study 2 (presented in Section 4), a non-collocated, fully online setting where there is no self-reporting involved.

3.3.4 Robustness -- Panel Data Analysis for Treatment Effects

This experiment has time varying treatment durations from two sources. Firstly, in purely exogenous fashion, the treatment is applied to existing users at the start of the experiment and to incoming users during the course of the experiment. Secondly, because of the incentive period resetting feature (a practical consideration on the part of the gaming company to maximize adoption) in the design, the treatment, as discussed before, potentially has endogenous, time varying treatment durations at the individual level.

Therefore, I checked the empirical distribution of the treatment periods across the cells for the full duration of the experiment and found no significant difference in the balance of the panels as shown in the Tables 6. The analysis variable, *incentivized_period_num*, in Table 6 captures the number of days a user of a given group spent in the active incentivized phase.

Testgroup	*incentivized_period_num*		
	Mean	**Std Error**	**Std Dev**
Control	8.1718	0.1136	2.2253
T0: No reward, but reminders	8.1347	0.1164	2.2417
T1: Selfish reward	8.1690	0.1142	2.1523

T2: Equal reward	8.3056	0.1063	2.0525
T3: Generous reward	8.2983	0.1455	1.9577
p value for joint test			0.7821

Table 6 : Treatment periods across the groups for the full duration of the experiment

While in aggregate the treatments duration distributions appear identical across treatments, I use the individual level panel data to get a more robust treatment effect estimation, using fixed effects (justified below) to take into account time-invariant individual heterogeneity. The panel data is based on the information recorded about the organic users of the mobile game app in the various treatment groups. On every day *t*, I have collected the following data (Table 7), for each user:

Notations	Variable Descriptions
$AdoptionCount_{i,t}$	Number of invites by user *i* at time *t*
$Treatment\_N_{i,t}$	Whether the user *i* in treatment group *N* is in the incentivized period (1 = incentivized period, 0 = others)

Table 7 : Notations and Variable Description

The variables $AdoptionCount_{i,t}$ is my DV and $Treatment\_N_{i,t}$ is the indicator for treatment in a specific incentive group. In this real-world field trial, as mobile gamers are loath to provide personal data, I do not have any demographic data (*e.g.*, age, gender) about users. To evaluate the need for a fixed effects model, I performed the Hausman specification test (Greene 2008), which rejected the random effects model[20]. Therefore, I

[20] The Hausman test for random effects versus fixed effects has a m-value = 11.34, (Pr > m) <0.023, hence random effects model is rejected.

use a two-way fixed effect (time period δ_t, $and\ user\ \eta_i$) model with individual and time dummies as below[21]:

$$AdoptionCount_{i,t} = \alpha_0 + \alpha_1 Control_{i,t} + \alpha_2 Treatment\_0_{i,t} + \alpha_3 Treatment\_1_{i,t} + \alpha_4 Treatment\_2_{i,t} + \alpha_5 Treatment\_3_{i,t} + \delta_t + \eta_i + \varepsilon_{i,t} \quad (1)$$

I present the results on the coefficients of the two-way fixed effects model for all organic users in Table 8, which shows the treatment effects of different incentive schemes on number of invites. Among the three types of incentive schemes, the estimates show, that generous rewards scheme is positive and significant at the 5% level and the split scheme is marginally significant. Robustness checks with the $GameCount_{i,t-1}$ and *Game_total_player* variables, which show similar qualitative results, are provided in Table 19, 20 of Appendix A.

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0033	0.0145	-0.23	0.8179
T0 (No reward, but reminders)	0.0012	0.0018	0.69	0.4897
T1 (Selfish)	0.0009	0.0018	0.51	0.6067
T2 (Equal Split)	0.0033*	0.0018	1.85	0.0646
T3 (Generous)	0.0072***	0.0017	4.07	<.0001
Observations	34493			
R^2	0.0877			

Table 8 : Effect of different incentive schemes on number of invites

[21] The Wald test for joint significance of time-dummies marginally rejects the null hypothesis (p = 0.0591) that they are all insignificantly different from zero, and hence, a two-way (individual and time) fixed effect model is preferred.

I also find evidence of heterogeneous treatment effects for the generous cell depending on whether the user is a new user or an existing user. In the interest of brevity, the details are in Appendix B.

3.3.5 Robustness – Eliminating the Treatment Resetting Period

Finally, as a further means of eliminating any bias in our treatment effect due to potentially endogenous treatment durations caused by the resetting of the incentivized period, I check the sensitivity of these results by restricting the incentivized period to the first seven days in the experiment phase. In this phase, there is no resetting whatsoever and all users are equal in terms of being in incentivized treatment period and, of course, randomly assigned.

In comparison to the previous results of the aggregate data based t-tests and Poisson regression, but along the lines of the panel data estimation of the previous sub-section 3.3.4, this analysis allows me to see that both the equal split reward and generous reward schemes are significant in increasing the number of invited adoptions. Overall, the panel data models not only pick up the causal relation between the incentive schemes and the net count of invited adoptions, but also exploit the temporal information of which types of users (*i.e.*, new versus existing) respond more to which type of incentive schemes, and thus yield a more precise treatment effect.

In the strictest (most conservative) inference test of the treatment, when I rely on only the first seven days of the treatment period (to avoid potentially endogenous unequal treatment durations of the field experiment), I find that the generous treatment is 2.2 times (Wald Statistic = 4.16, $p = 0.0414$) more effective as compared to the selfish treatment and 1.6 times (Wald Statistic = 2.36, $p = 0.1243$) higher (but not statistically significantly different) than the split treatment in generating a conversion. Thus, it is clear that a budget-constrained marketer would choose to invest the marginal dollar in the generous incentive scheme over the selfish scheme.

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0041	0.0148	-0.27	0.7836
T0 (No reward, but reminders)	0.0011	0.0019	0.59	0.5585
T1 (Selfish)	0.0031	0.0019	1.66	0.1162
T2 (Equal Split)	0.0043**	0.0018	2.31	0.0212
T3 (Generous)	0.0069***	0.0018	3.79	0.0002
Observations	34493			
R^2	0.0872			

Table 9: Effect of incentive schemes in the first week of experiment

Although Study 1, based on a total-effect design with a mobile social game, allowed me to capture the overall effect of the different referral incentive schemes on offline WOM-based adoptions, its scope in revealing mechanism level insights into the incentive tradeoffs between the sender and the recipient is limited. This is due to the mobile environment's inability of tracking which group of senders sent out more offline referrals and because of its reliance on self-reported invitation attribution by co-located recipients. Therefore, to overcome potential complications arising from interactions among subjects in uncontrolled environments (Walker and Muchnik 2014; Aral 2016) and to derive additional insights into how each type of referral scheme influences the two metrics of interest – sending rates and acceptance rates of invitations – I conducted a follow up controlled experiment that addressed some of the mechanism level limitations and generalizability aspects of the previous study.

4. Study 2 - Controlled Laboratory Experiment

For this second study, I developed a web-based word game and used the subject pool from my university's behavioral lab[22] to replicate the treatments (i.e., selfish, equal-split, generous) of the previous field experiment[23]. The design of this study overcomes the challenges of the previous experiment, and in the process helps us better understand the underlying mechanisms, in two key ways:

(i) The referral process of the word game used an email-based invitation, which enabled authentication as well as tracking of the referrals sent out and accepted, thus avoiding any dependence on self-reported conversion outcomes.

(ii) The context is a single-player word game, which does not suffer from potential treatment interference and bias from user co-location.

Overall, results of the Study 2 show that in the context of non-collocated non-social all three incentives schemes beat the control group in generating new adoptions. What is interesting, however, is that digging deeper into the tradeoffs between incentivizing the receiver versus the sender of the referrals I find that a) there is no significant difference in the sending rates at the 5% level of significance (the selfish scheme is marginally significant at the alpha = 10% level), b) that the generous group has a significantly stronger effect on the receiver's likelihood of adopting (estimates are identical using clustered errors of random effects for the senders), and c) the conversion rate is significantly higher for the generous group. Thus, while at the aggregate level, in Study 2's context of non-social games, I find that all three incentives schemes are equally

[22] Although the participants were recruited using the behavioral lab's mailing list, this was not a typical lab study; it was an online, randomized, controlled trial of a simple word scramble game that I developed.
[23] I did not implement the reminders feature; hence the treatment with no reward but reminders is absent.

effective in bringing new adoptions, at the mechanism level, the results from this study demonstrate the efficacy of pro-social incentives over selfish schemes in generating referral conversions, as well as a presence of a significant, Leontief style, altruistic component in the subject's utility function. The result that there is no degradation in the sender's decision to initiate referrals as money is taken away from her and given to the sender indicates that such agents' utility is composed of both self-maximizing components and altruistic components in equal parts. This provides further evidence that a budget-constrained marketer should lean towards using referral incentive schemes that have a significant pro-social component in them, ceteris paribus.

4.1. Study 2 - Design Details

I developed a web-based word scramble game and recruited 71 participants from my school's behavioral lab mailing list to serve as the pool of senders who were to refer the game to their peers (i.e., the general member population at the University who were not in the lab's participant pool). This population is not inherently an unrepresentative pool for gaming as this segment can represent up to 25% of mobile game players[24]. All the 71 study participants as well as their recipients had to be affiliated to the University, and thereby in possession of a uniquely identifiable University email account that would have to be used in the game's login process. This allowed me to not only track the email invitations sent and authenticate the senders and recipients, but also prevent the creation of fake accounts for the study. To facilitate the referral process, I integrated a directory search feature in the game that allowed senders to lookup their recipient's valid email address and send an invitation mail with a standard template.

[24] http://www.vertoanalytics.com/chart-week-mobile-gamer-demographics/

The study participants (i.e., senders) were randomly assigned to one of the four groups, one control group and three treatment groups[25]. All of them received a $10 for creating an account on the game site and playing the game[26]. Any additional rewards earned by a participant for each successful referral depended on the treatment group to which that individual had been assigned. A successful referral was defined as being one where a recipient signed up for the game by creating an account with their email on the web site[27]. For each successful referral, participants assigned to the selfish group (Group 1) received $3 while participants in the equal split group (Group 2) received $2 and participants in the generous group (Group 3) received $1. Recipients of participants in the selfish group, equal split group, and generous group received $1, $2 and $3, respectively. Those assigned to the control group had the same option to invite their friends by email but received no additional compensation for the referral. Recipients did not have the option to invite others.

The referral period lasted for a week and the study was conducted entirely online, thus eliminating the need for the participants to gather for pre-study briefings and reducing the possibility of contamination across treatment groups. Figure 4 shows the screenshot of the word game and Figure 5 shows the referral page for selfish treatment group.

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[25] I ensure that the senders are well balanced across all the covariates

[26] All compensations were given out using Amazon eGift cards at the end of the experiment

[27] To prevent fraudulent signups, I checked in real-time on the recipient's email address against the database to ensure that this email account that was being used in the sign up process was valid and indeed one to which an invitation had been mailed by one of the senders. If a receiver accepted invites from multiple senders, then they were excluded from the study.

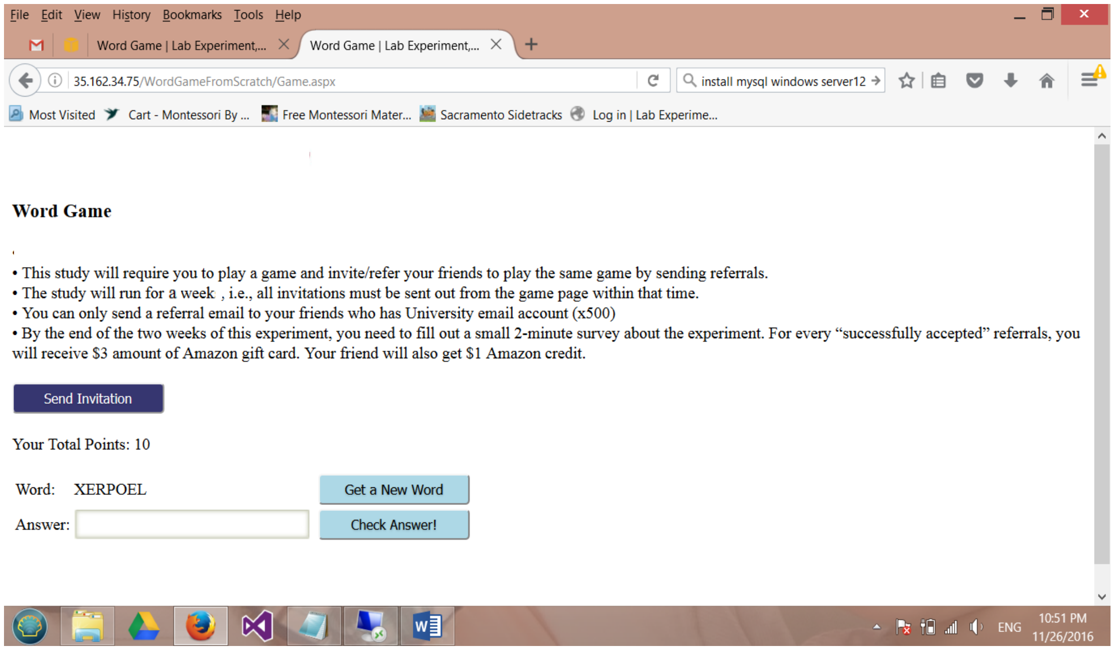

Figure 4: Screenshot of the Word Game and Referral Prompt for Selfish Treatment

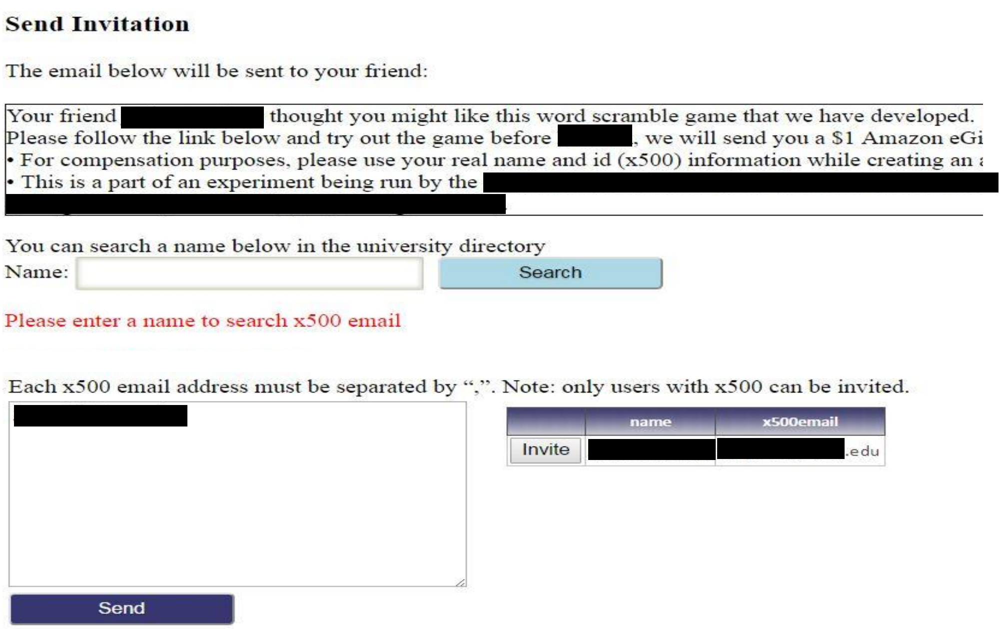

Figure 5 : Screenshot of the Referral Invitation Page

4.2. Study Results

To identify the effect of different incentive schemes on both sender's likelihood to send and the recipient's likelihood to accept referrals, I run the regression both at the sender level and recipient level (Duflo et al. 2008, Duflo et al. 2011).

First, I relate the count data on the number of invitations sent by a sender (*invite_num_sent)* to dummy indicators of each of the treatment conditions (Equation 2) and run a negative binomial regression at the sender level to analyze the relationship between incentive schemes and the sender's referral behavior (Equation 2)[28].

$$\mathrm{Log}(Invite\_num\_sent_j) = \alpha + \sum \beta_j T_j + \varepsilon_j \quad (2)$$

$$\mathrm{Log}(Invite\_num\_converted_j) = \alpha + \sum \beta_j T_j + \varepsilon_j \quad (3)$$

Table 10 shows the results for the effect of the incentive schemes on the number of referrals sent by study participants (i.e., senders) to their friends. I find that there is no significant different at the alpha = 0.05 level across the treatments in the sender's referral behavior.

Parameter	**Estimate**	**SE**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept	0.2076	0.3765	-0.5302	0.9455	0.3	0.5812
Group 1 (Selfish)	0.9531	0.514	-0.0544	1.9606	3.44	0.0637
Group 2 (Equal)	0.5046	0.5206	-0.5159	1.525	0.94	0.3325
Group 3 (Generous)	0.5808	0.5242	-0.4466	1.6082	1.23	0.2679

Table 10: Effect of incentive schemes on the number of referrals

This is a somewhat surprising result, especially if I assume purely economic rational agents. Ex ante, I might expect the referral rate should decline as money is taken away from senders and given to recipients in the equal and generous treatments, i.e. when

[28] Goodness of Fit results show that negative binomial model form fit our data (Chi2(99) = 73.52, p = 0.97418) while Poisson model does not (Chi2(99) = 485.119, p = 0). Results using OLS are also provided in Appendix C.

they receive smaller incentives with altruistic approaches. Instead what I observe is that the effect of monetary loss is being supplemented by the gain from altruistic utility, and that self-regarding and other-regarding two components of the utility are acting as pure substitutes in a Leontief manner.

Subsequently, I run the regression (Equation 3) to analyze the relationship between various incentive schemes and the successful referral outcomes (*invite_num_converted*) as well as on the recipients' decision to adopt. The results are for the former are reported in Table 11. The results show that all three incentive schemes significantly increase the number of successful referrals compared to the control group, with the generous and split treatment having a slightly higher (but not statistically distinguishable) effect than the selfish scheme.

Parameter	**Estimate**	**SE**	**Wald 95% Confidence Limits**		**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-1.3122	0.4723	-2.2378	-0.3865	7.72	0.0055
Group 1 (Selfish)	1.4214	0.5811	0.2824	2.5604	5.98	0.0145
Group 2 (Equal)	1.4553	0.5802	0.3182	2.5924	6.29	0.0121
Group 3 (Generous)	1.4606	0.5839	0.3162	2.605	6.26	0.0124

Table 11: Effect of incentive schemes on the number of adoptions

In contrast to the previous experiment with the mobile social app, the selfish scheme has a significant effect in this word game. This may be attributable to the fact that the participants recruited from the behavioral lab may be more eager to receive monetary rewards and the online referral setting provides less reason for them to feel guilty about deriving monetary rewards from the referral process.

Further, the detailed online data allows me to derive some additional insights into the underlying effect of the referral schemes on the sending and acceptance rate of referrals. Especially, I find that the conversion rate of referrals sent from equal split group and generous group is 62% and 51% higher than the conversion rate of the selfish group, which is 159% and 141% higher than the conversion rate of the control group. Figure 6 shows that this difference is statistically different. Given that all three schemes have similar sending rates, a higher conversion rate in the pro-social scheme is an interesting finding that deserves further investigation.

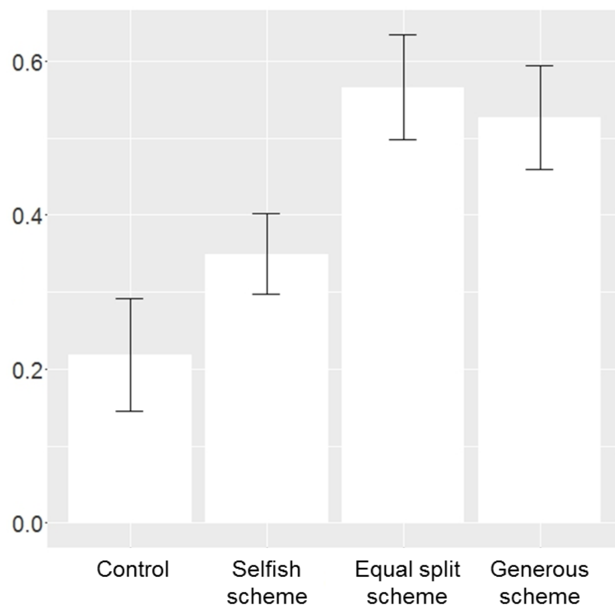

Figure 6: Referral conversion rate of each group

I further drill down and find that this higher conversion is driven by the impact of incentive schemes on recipient's decision to accept. A random effects model (following Bapna and Umyarov 2016) at the recipient level is tested using the specification in Equation 4. $Decision\_to\_adopt_{ij}$ indicates recipient's i's decision to adopt after receiving sender's j's referral.

$$Decision\_to\_adopt_{ij} = \alpha + \sum \beta_j T_j + \varepsilon_{ij} \tag{4}$$

The results are reported in Table 12, which shows that only the equal split and generous treatments are significant in driving referral conversions. Thus, at the recipient level it appears to be the case that the adoption follows the rational economic paradigm. Recipients respond more favorably when they revive a larger monetary share. Overall, taking the two studies together, it is clear that a budget-constrained marketer who is trying to maximize the size of the user base should use an altruistic scheme even if it is to just provide higher incentives for new adopters. As I showed earlier in this section the altruistic schemes do not reduce the incentives to send out the invitations, in other words referrals are either positively or non-negatively affected by the altruistic design, and given that the adoption follows the rational economic paradigm, using an altruistic design is better.

Effect	Estimate	SE	t Value	Pr > |t|
Intercept	0.235	0.06363	3.69	0.0003
Group 1 (Selfish)	0.09105	0.07715	1.18	0.2388
Group 2 (Split)	0.2113	0.08506	2.48	0.0135
Group 3 (Generous)	0.1738	0.08226	2.11	0.0354

Table 12: Effect of incentive schemes on the referral acceptance by recipients

These results together provide some insights into how a decision maker should think about the various tradeoffs induced by the referral incentive schemes they choose and suggest that the some of the incentive amounts from the sender can indeed by diverted to the receiver without hurting the sending rates. The results are robust across alternative specifications at both levels, including count models at the sender level and binary outcome model at the recipient level. Specifically, I obtain consistent results using

Poisson model at the sender level and linear probability model as well as probit and logit models at the recipient level (see Appendix C, Table 27-30).

5. Discussion

Understanding how incentive structure causally impacts the diffusion of products through both offline and online WOM is a crucial step in developing referral reward strategies for viral adoption of digital goods. Given that a successful referral required positive action from both a sender and a recipient, any incentive mechanism that aims to accelerate organic WOM has to delicately balance the tradeoff between rewarding the sender and the receiver. I explored this issue by designing two related but contextually different studies in which I tested the effectiveness of selfish, equal, and generous referral rewarding schemes. The context of Study 1 was a mobile social game application with no prior brand history and other priming effects, which allowed me to design a clean study on the effect of *online referral reward structure* on the *offline diffusion* of the product. Study 2 allowed me to dig deeper into the underlying mechanisms as it did not suffer from some of the measurement limitations of tracking offline word-of-mouth in a mobile environment. In Study 2, I developed a web-based word game and used the subject pool from my university's behavioral lab to replicate the treatments (i.e., selfish, equal-split, generous) of the previous field experiment. Study 1 is unique and distinct in the IS literature in its use of geo-sensing based measurement to capture offline word-of-mouth. However, it also poses two specific challenges. Firstly, Study 1's design does not capture the differential effect of the treatments on the sending of referrals. Further, because of the co-location based nature of the game the outcome is self-reported and the recipients' propensity to report could be correlated to treatment. Study 2 overcomes these limitations and takes place in a non-colocation/social based gaming context. The entire referral process is implemented online and allows for full tracking at the sending and accepting sides, without the need for self-reporting.

Overall, taking the two studies together, the results suggests that a budget-constrained marketer who is trying to maximize the size of the user base should use an altruistic scheme even if it is to just provide higher incentives for new adopters. I find that altruistic schemes do not reduce the incentives to send out the invitations, in other words referrals are either positively or non-negatively affected by the altruistic design. This coupled with the fact that the recipients' adoption behavior follows the rational economic paradigm, it becomes evident that using altruistic pro-social component is advisable. I observe that in contrast to expectations of behaviors by rational economic agents, the altruistic design does not reduce sender participation, implying that senders do not act from purely economic perspective and that their utility has explicit valuation for altruism.

This work complements two streams of prior research on viral marketing: estimating causal peer influence in social networks, and constructing referral incentive schemes to promote WOM based adoption. Although previous studies using randomization trials have demonstrated peer influence at work, there hasn't been much empirical investigation to discover how different referral incentive schemes drive the peer influence in the social contagion process. Existing studies of designing referral incentives on WOM mainly focused on senders' behavior and rarely considered incentive sharing schemes in which both parties may receive rewards. I contribute to the literature by studying how an important mechanisms of social contagion, online and offline word of mouth, are causally influenced by the design of the referral incentive scheme, namely, selfish reward, equal split reward, and generous reward schemes. The findings of the study are thus relevant to creating referral programs to promote WOM based adoption of digital goods.

Essay 2: Altruism Pays! Towards Optimal Call-to-Action for Online Referral

1. Introduction and Theoretical Background

Concomitant with the exploding growth of digital social networks and the importance of word-of-mouth, firms recognize the importance of using referral programs towards driving new business. Such schemes encourage existing customers with an incentive-laden call-to-action to engage their social networks by informing them about products and ultimately influencing and stimulating friends' purchase decisions. While referral marketing is a widely adopted practice, the underlying science behind understanding and optimizing its various dimensions is nascent. As an example, while call-to-action design for online referral to the sender is one of the key design choices for the optimal design of online referral programs, no study has investigated how firms can optimally design the call-to-action to engage customers in initiating referrals in the first place. Given the increasing importance of online referral programs, it is crucial to close this gap. Therefore, in this essay, I tackle the question of the optimal design of the call-to-action for online referrals.

My perspective in approaching this design question is theoretical. As mentioned above, I view online referrals as incentive-laden word-of-mouth mechanisms. The fundamental building block of successful word-of-mouth based product diffusion is delight among the existing base of customers (Kornish and Li 2010), which then is communicated to relevant portions of their social networks, whose actors within might also, ostensibly, experience similar delight, benefit, or gain positive utility from adopting the focal product. This concern for the benefit of the other suggests that a necessary condition for successful online referral is the altruistic consideration of the sender towards the recipient's welfare in adopting the product. Of course, it is well known that individuals may themselves derive significant non-monetary payoff from helping others in the form of either pure altruism or warm-glow (Andreoni 1988, 1990). Thus, an altruistic call may enhance customers' pure or warm-glow altruism, and therefore encourage more sharing from them. Prior literature also suggests that an altruistic call may reduce customers' psychological cost of feeling guilty about gaining referral rewards (Rue and Feick 2007). Taken together, these theoretical ideas suggest that an altruistic frame of mind is likely to result in higher quality of advocacy which might be associated with reduced guilt in receiving a monetary award for someone else's action, better targeting of people who are more likely to receive positive utility from the product, greater effort in communicating the potential benefits, or, some mixture of these. Yet, a close look at influential referral programs in the practice[29] reveals that companies do not necessarily hone in on this theoretical insight and exhibit significant heterogeneity (or, arguably, lack of thoughtfulness) in their design of all three aspects of online referrals. Consistent with the above theoretical argument, the results of my first essay show that an altruistic component in the incentive scheme, either via splitting the incentive equally between the sender and the recipient or purely rewarding the recipient, significantly outperforms purely rewarding just the sender. Sun et al. 2015 finds that when a single-use promotional code targeted to the customers is made shareable, a significant portion of customers is willing to pass on the code to their friends, rather than using it themselves.

[29] Please see an excellent summary of influential referrals programs (http://www.referralcandy.com/blog/47-referral-programs/), including links to referral programs run by leading firms like Paypal, Uber and Airbnb e.g. https://www.airbnb.com/invite)

With respect to the framing of the call-to-action, the focus of this study, the current state of affairs reveals that while companies are seen to be 'experimenting' with multiple types of call-to-action for online referrals, the 'altruistic' call-to-action, honing in and emphasizing the recipients' monetary benefit, is, anecdotally, seldom observed[30]. This is potentially driven by firms' perception that the sender may be more likely to initiate a referral if her own, ostensibly monetary, benefit is highlighted. In line with this thinking, I see a prevalence of what I call the 'egoistic' call-to-action, where the firm highlights the reward (often a discount coupon or cash incentive) to the sender, and, also in several cases, what I call an 'equitable' call-to-action, where the firm highlights that both sender and her friends get the reward. While the exact distribution of the usage of these three types of call-to-action is unknown due to lack of comprehensive proprietary data[31], what is more interesting from a research perspective is a controlled scientific 'horse-race' between these three schemes and a generic call-to-action, which will serve as the control group. I conduct this horse race using the methodology of a randomized field experiment (Aral and Walker 2011b, Bapna and Umyarov 2016, Ghose et al. 2015) that is becoming the gold standard in the information systems literature.

As mentioned earlier, I am particularly interested in the role of altruistic framing[32] in driving customer's referral decision and related outcomes as it contradicts conventional wisdom, and the observed norm in practice. Perhaps driven by an over

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[30] The argument is based on observations of more than 400 A/B testing conducted by the companies on the one of the largest referral platform in the past 6 months

[31] However, a quick search over the referral programs and promotional emails conducted by major companies in Airline (e.g. Southwest), Credit Card (Chase Freedom, Sapphire) and Hotel Chain industry (Hilton, Marriott) industry shows that egoistic framing is dominating. Almost all emails promoting referrals program in those companies adopt egoistic framing in their title.

[32] From now on I use the word "altruism" to cover both warm glow and pure altruism (Andreoni 1990)

emphasis on *homo-economicus* styled, self-maximizing thinking from economics, the industry norm is to emphasize the benefit of the referral incentive to the senders to stimulate their act of referring. However, there is reason to believe that this can be counter-productive, as highlighting of one's own reward may increase psychological and social cost of the sender by creating a feeling of guilt (Ryu and Feick 2007, Smith et al. 1999). On the other hand, as discussed above, customers may derive non-monetary payoff if they care about friends' payoff (pure altruism) or about the referral action itself (warm glow). If altruism plays an important role in referral behavior, then I would expect the altruistic call might significantly increase a sender's likelihood of sharing, since customers who share because of specific motive (e.g. altruism) will more likely respond to the corresponding framing (e.g. emphasizing altruism). However, if the argument of the friend's interest is taken a step further, it can be the case that the existing customer will become more selective in referral as they care and deliberate more about friend's payoff from purchasing the focal product (Kornish and Li 2010). Thus, the altruistic call might also lead to lower likelihood of sharing and fewer shares by the senders because it becomes harder for them to identify potential recipients. Given the mentioned tradeoffs and theoretical predictions, it becomes interesting to test in the field whether altruistic framing always leads to larger volume of referrals or not. Specifically, I test the following hypothesis via the research design:

Null hypothesis 1A(Main effect): The three types of calls-to-action, egoistic, equitable, and altruistic, are indistinguishable from each other and the control group with respect to the volume of word-of-mouth referrals.

Alternate hypothesis 1A(Main effect): The altruistic call-to-action outperforms the control, egoistic and equitable calls-to-action with respect to the volume of word-of-mouth referrals.

Regarding the outcome of the referrals, as mentioned above, if customers become more selective in referral because of altruism, the altruistic call is likely to result in fewer referral outcomes. However, this potential downside can arguably be counter-balanced by the fact that conditional on the referral decision, such selective referrals driven by altruism may be better targeted and therefore result in a higher conversion rate than those driven by other motives, such as the equitable and selfish. I thus hypothesize and test the following:

Null hypothesis 1B(Main effect): The three types of calls-to-action are indistinguishable from each other and the control group with respect to the outcomes of word-of-mouth referrals, i.e. total number of successful referrals.

Alternate hypothesis 1B(Main effect): The altruistic call-to-action outperforms the control, egoistic, and equitable calls-to-action with respect to outcomes of word-of-mouth referrals.

If altruism is an important driver of online referrals, I should see the higher impact of altruistic framing for customers with a higher affinity of the product, as customers will care more about their friend's utility and in this case, customers will project their own evaluation onto others (Cronbach 1955; Ichheiser 1946). Thus, those customers with a higher affinity may be more likely to infer that their friends would also gain benefits or positive utility from the product; thus are more likely to share. Customers with high affinity of the product can be represented by the number of repeat purchases (Hoyer, 1984) and by a high reported net promoter score (hereafter, NPS) (e.g. willing to share the product) (Reichheld 1996). Thus, I test the following hypothesis by exploring the heterogeneity in treatment effect:

Null hypothesis 2A(Mechanism): Customer affinity of the product, as measured by the repeat purchases and their net promoter score, will not significantly moderate the effect of three types of calls-to-action on referral behavior.

Alternate hypothesis 2A(Mechanism): Customer affinity will, uniquely, positively moderate the effect of the altruistic call-to-action on referral behavior.

Furthermore, I expect the effect of altruistic framing may be depending on the recency of customers' last purchase, whereas the effects of other framings are less so. This is likely to happen because sharing under altruistic considerations is more driven by intrinsic delight and enthusiasm for the product (Kornish and Li 2010), rather than external incentive; but such delight/enthusiasm (to share the product) may decay over time after customers' purchase (Berger and Schwartz 2011). Thus, I expect the effect of altruistic framing, which is closely related to the altruism in sharing, would be highest for customers who purchased and got the product recently, and would be lower for customers who made the purchase a while ago. In contrast, I expect the effect of egoistic framing, which provokes referrals with external incentive, on referral behavior won't decrease over time compared to other framing as the external incentive for customers to make referral is independent of when the customers made the last purchase. In other words, the value of material payoff will never decay but intrinsic motivations will. I thus hypothesize and test the following:

Null hypothesis 2B(Mechanism): The recency of the past purchase, as measured by the time since latest purchase, will not significantly interact with the three types of calls-to-action on customers' referral behavior.

Alternate hypothesis 2B(Mechanism): The recency of the past purchase will positively moderate the effect of the altruistic call-to-action on customers' referral behavior.

In addition, aligned with the theorizing about the mechanism underlying the effect of different calls-to-action, I expect the motives to share and not to share would also be different across groups. Specifically, I hypothesize that altruistic framing would reduce the sender's guilt from engaging in referral program with incentives, especially compared to other framings (Ryu and Feick 2007). It is also likely that those who share under altruistic framing are more likely to focus on the benefits of others (i.e. family/friends), rather than one's own payoff. As an outcome, those customers may also become more selective in referral as they care and deliberate more about their friend's payoff (Kornish and Li 2010). Therefore, with the objective of uncovering the underlying motives that distinguish the success of a particular type of call-to-action, I test the following:

Null hypothesis 3 (Motive): Customer motives will not significantly vary across the three types of calls-to-action.

Alternate hypothesis 3A(Motive): Customers targeted with the altruistic call-to-action will report lower levels of guilt and be more selective in identifying friends who will benefit from the shared product.

Alternate hypothesis 3B(Motive): Customers who share referrals under the altruistic call-to-action will be more likely to identify family and friends' benefits as the motive, and less likely to identify their own benefits as the motive for sharing.

In this essay, I posit, test, identify, and understand the underlying motives behind the optimal call-to-action for online referrals. I do so in collaboration with a large US based online platform specialized in photo processing and related products (their revenue for 2015 was $22 million). I conduct a large randomized field experiment involving 100,000 customers to test the impact of three afore-mentioned call-to-actions. I fix the incentive design of the referral program as equal-split as well as the recipients' message and only vary the call-to-action to the senders in the experiment. I am interested in identifying the causal effect of the framing of the calls-to-action on customers' referral decision, whether they share and to what extent they share, as well as on their induced referral outcomes as measured by the number of successful referrals. Specifically, I randomly assign 100,000 customers who have made purchases on the platform in the past 4 months into four test groups (10,000 in control and 30,000 in each of the three treatment groups), and email each group with different calls-to-action (Figure 7). I collected data on customers' referral behaviors and outcomes within a 5-week window after the experiment. I further augmented the data from field experiment with rich archival data, including product characteristics, individual characteristics, their past purchases and their NPS scores. I also conduct a large-scale post-experiment survey to understand why customers in the experiment share or don't share after receiving the call-to-action. The data from the randomized experiment, the archival data, and the survey allows me to identify the causal effect of different calls-to-action as well as to explore the underlying mechanisms.

The primary finding, consistent across multiple econometric specifications, is that, in line with the theoretical prediction and in contrast to conventional wisdom, the altruistic framing of the call-to-action for initiating a referral is most effective in driving referral behavior and resulting in the best outcomes for the firm. Compared to the control group with information about the fixed incentive scheme, the email that highlights friends' reward significantly increases not only the likelihood of sender making referrals, but also the total number of successful referral purchases. In addition, I find that the effect of altruistic framing is significantly higher than the effect of egoistic framing and equitable framing across all the referral behaviors and outcome (***Hypothesis 1A, 1B)***. Secondly, I find large heterogeneity in treatment effects across different customer segments, yielding interesting insights into the underlying mechanisms that support the main finding. Specifically, consistent with the underlying theoretical premise of customer delight as a necessary condition for effective word-of-mouth, I find that the altruistic framing is more effective for users who made repeat purchases in the past and for those that reported higher NPS scores (***Hypothesis 2A)***. This is aligned with the notion that customers who have higher level of product and brand affinity are more likely to share it with their friends for altruistic purpose as they believe their friend would also like the product and derive benefit from the purchase. Finally, I find that the effect of altruistic framing is positively moderated by the recency of the purchase (***Hypothesis 2B)***. In contrast, I did not observe such significant decay for other types of framing that highlights the referral incentive to the sender. This is consistent with the fact that customers' inherent enthusiasm to talk about the product may decay over time after new purchase (Berger and Schwartz 2011).

I further investigate the underlying motives by conducting a post-experiment survey. The results from the survey suggest that an altruistic call-to-action for online referrals is associated with a reduction in customers' feeling of guilt in making referrals compared to control and egoistic call-to-action but is not linked with the perceived difficulty of finding a friend who may like the product compared to control and equitable call-to-action (***Hypothesis 3A)***. I also find that customers who are under altruistic framing are more likely to report that friends and family might be happy with the promotion as their motive of sharing (***Hypothesis 3B)***. Overall, the evidence suggests that altruism is important in driving online referral and it can be spurred by an altruistic call-to-action.

In addition to the theoretical contributions, this essay also provides clear managerial implications for firms. Based on the results from the experiment and survey, I offer concrete guidance to firms on how, to whom, and when they should initiate call-to-action for a referral, as well as why they should do so. Firstly, the main results suggest that in contrast to conventional wisdom, firms should more frequently use altruistic framing in their call-to-action as compared to the status quo of current practice. Secondly, the findings of large heterogeneity in treatment effects across different customer segments suggests that, given the costs associated with referral marketing, firms should target customers with higher affinity first in their referral campaign. Thirdly, regarding to the timing, firms should send out an altruistic call-to-action for referral to customers shortly after their purchase. Finally, the results from the post experiment survey suggest that when designing the referral program, firms should try to reduce the guilt feeling of customers and to enhance the altruism to drive not only more but also more effective referrals. Interestingly, as I discuss in the conclusion, the optimal call-to-action for a referral also complements the optimal call-to-action for purchase (on how, to whom and when to call). Taken together, these insights have the potential to significantly impact and alter firms' marketing communication. In fact, based on the results of the experiment, the altruistic call-to-action (along with the timing and targeting strategy) has been implemented by the collaborating platform (Collage.com), impacting hundreds of thousands of customers each year.

This essay draws from and contributes to several streams of literature at the intersection of information systems, marketing and economics. First, the study enriches the literature on digital word-of-mouth by identifying the causal effect of a call-to-action – one of the key elements in online referral programs. Although, designing key elements of an online referral program to drives social contagion has been of much interest to both academics and practitioners, identifying the causal effects of different design are methodologically hard because of endogeneity (Manski 1993). Using a large scale randomized experiment, I show that, in contrast to the conventional wisdom and current practice, altruistic framing works best in driving online referrals. A minor change in framing may lead to significant increase in referral revenue. In this way, this essay also closes the gap of identifying the optimal design of online referral program (with my first essay on optimal incentive structure and Sun et al. 2014 on optimal message design).

This essay is also among the first to provide insights on the underlying motives of senders' online referral. Specifically, the study provides concrete and causal support to the hitherto under-studied role of altruism in creating word-of-mouth. In the IS literature, a few studies have analyzed motives of online behaviors such as community participation and found that they are likely to be driven by altruism (Bitzer et al. 2007, Anderson and Agarwal 2011, Jabr et al. 2014, Xia, Huang, Duan, and Whinston 2012). However, despite the large volume of online referrals, little is understood about its underlying motives, as well as how companies can leverage such motives. This study, taking advantage of a randomized field experiment, and including a detailed analysis over multiple moderators and a large-scale survey, presents strong and consistent evidence that altruism is crucial in driving online referrals. This work also provides clear guidance on how firms can leverage altruism to improve online referral behavior and outcomes.

2. Institutional Details and Experimental Design

Along with my first essay, the initial idea of the experimental design comes from both the practice as well as seminal research in economics and social psychology that categorizes individuals into three categories based on their self and other regarding preferences (Andreoni and Miller 2002). The stream of literature shows that individuals can either be purely self-regarding, or caring about others' benefits only as much as they care about themselves, or purely other-regarding. In line with this insight and my theorizing earlier, I test the effect of three different calls-to-action for online referrals: a) the egoistic call-to-action, where the framing highlights and emphasizes the reward to the sender, b) the equitable call to action, where the framing highlights and emphasizes that both sender and the receiver get the reward, and c) the altruistic call-to-action, where the framing highlights and emphasizes the reward to the receiver. I am especially interested in the role of altruism as discussed in the hypotheses.

The research site is an online platform, Collage.com, where users can design a collage by uploading photos and customizing the layout with the proprietary software tools. Once a user creates the layout, she can purchase various types of customized printed products, such as blankets, photo-books, canvases, etc. A large number of customers purchase a variety of products from the platform every day. The annual revenue of the platform is more than 22 million USD and the number of purchasers exceed more than 500,000 transactions per year. Given the volume of sales and the customer base, even a small increase in existing customers' referrals would lead to a large increase in the firm's revenue. Like many other specialized digital platforms, the platform does not have an existing online referral program at work but is strongly interested in its potential.

For the experiment, I create four versions of emails and the webpage by varying only the framing of the same incentive scheme, namely, the equal-split incentive scheme in which both sender and receiver get the identical reward (a 70% discount coupon). I randomly draw 100,000 unique customers who have purchased products in the previous 4 months, and randomly assign them into one of the four test groups as per Figure 7. Then, I target the customers in the different groups with emails that only vary in their call-to-action for initiating the referral process. *All other factors, including the equal-split incentive schema for the sender and the recipient and the message received by the recipient, ie what the recipient knows about the program, are kept constant across the four cells of our experiment.* In each email, I change the email's subject, highlight different aspects of the same incentive scheme in the given context, and use different wording in the call-to-action button (Figure 8, 9). Once the customers click on the 'call-to-action' button in the email, they are directed to webpages with the consistent framing where they can send a referral to their friends. It is important to note that the same incentive scheme was offered to all participants across groups and the only difference is the framing of the referral program. Thus, the difference in customers' referral behavior and outcomes can be attributed to such difference in framing.

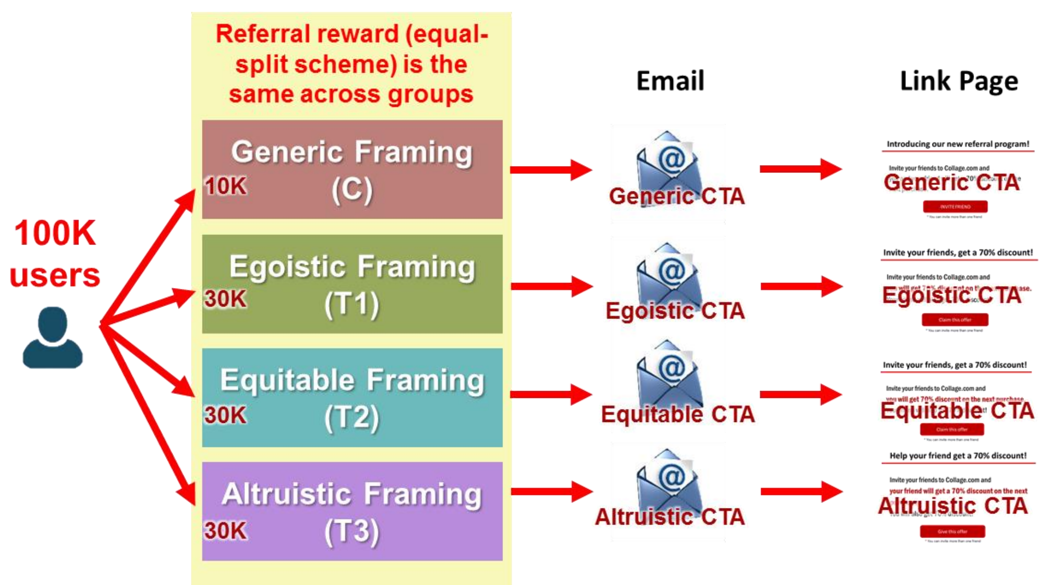


Figure 7 : Illustration of the Experiment Design

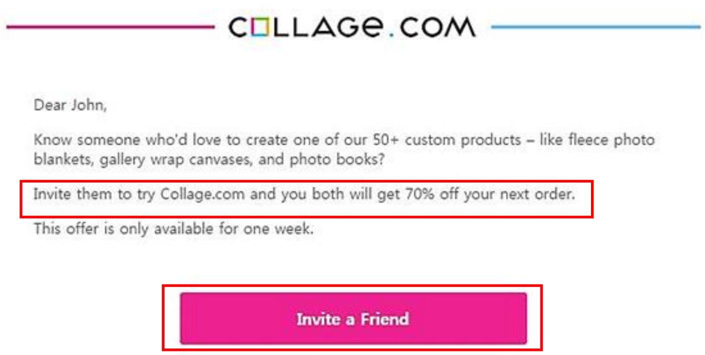
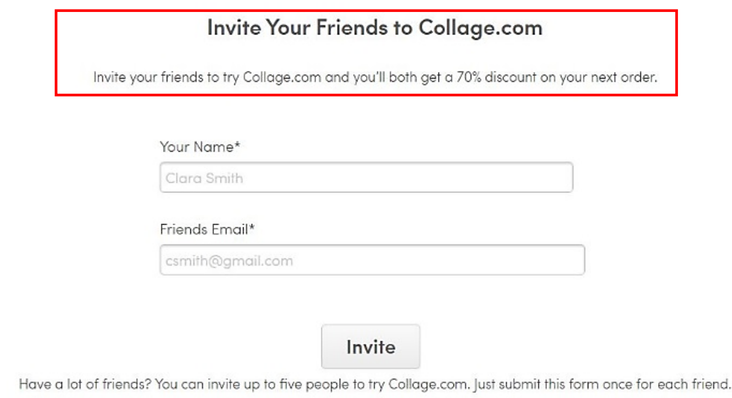
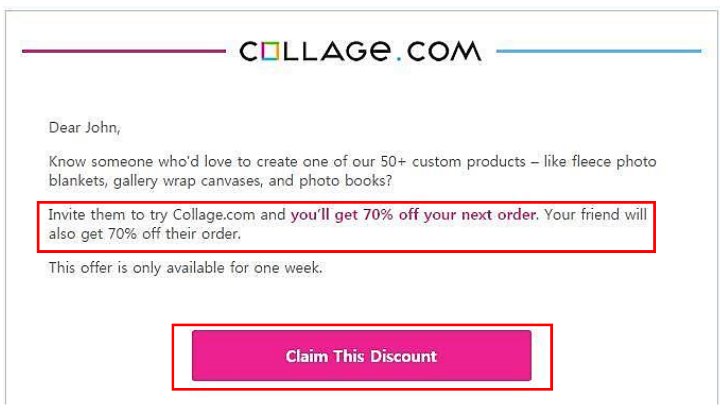
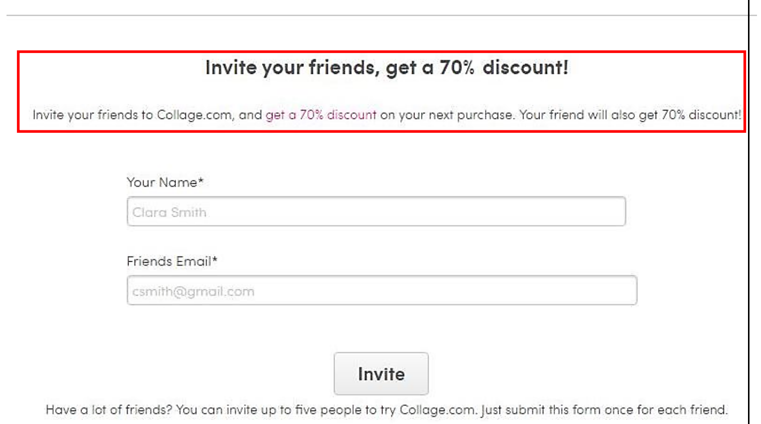
Group	Subject and content of the email	Content of the link page
No framing (C)	Subject: **The Collage.com Referral Program** Contents:  COLLAGE.COM Dear John, Know someone who'd love to create one of our 50+ custom products – like fleece photo blankets, gallery wrap canvases, and photo books? Invite them to try Collage.com and you both will get 70% off your next order. This offer is only available for one week. Invite a Friend	 Invite Your Friends to Collage.com Invite your friends to try Collage.com and you'll both get a 70% discount on your next order. Your Name* Clara Smith Friends Email* csmith@gmail.com Invite Have a lot of friends? You can invite up to five people to try Collage.com. Just submit this form once for each friend.
Egoistic Framing (T1)	Subject: **Invite your friends, and get yourself 70% off** Contents:  COLLAGE.COM Dear John, Know someone who'd love to create one of our 50+ custom products – like fleece photo blankets, gallery wrap canvases, and photo books? Invite them to try Collage.com and you'll get 70% off your next order. Your friend will also get 70% off their order. This offer is only available for one week. Claim This Discount	 Invite your friends, get a 70% discount! Invite your friends to Collage.com, and get a 70% discount on your next purchase. Your friend will also get 70% discount! Your Name* Clara Smith Friends Email* csmith@gmail.com Invite Have a lot of friends? You can invite up to five people to try Collage.com. Just submit this form once for each friend.

Figure 8: Example of Email/Link Page Received by Each User in Control/Egoistic Framing Groups

* Note: I highlight the difference in framing across different test groups using box of red solid line

Group	Subject and content of the email	Content of the link page
Equitable Framing (T2)	Subject: **70% off for you and a friend!** Contents: COLLAGE.COM Dear John, Know someone who'd love to create one of our 50+ custom products – like fleece photo blankets, gallery wrap canvases, and photo books? Invite them to try Collage.com, and **you and your friend, both will get 70% off** on the next order. This offer is only available for one week. **Share This Discount**	**70% discount for you and your friend!** Invite your friends to Collage.com, and you and your friend both will get 70% discount on the next purchase. Your Name* Clara Smith Friends Email* csmith@gmail.com **Invite** Have a lot of friends? You can invite up to five people to try Collage.com. Just submit this form once for each friend.
Altruistic Framing (T3)	Subject: **Give your friend a 70% discount!** Contents: COLLAGE.COM Dear John, Know someone who'd love to create one of our 50+ custom products – like fleece photo blankets, gallery wrap canvases, and photo books? Invite them to try Collage.com and **your friend will get 70% off their next order**. You will also get 70% off your next order. This offer is only available for one week. **Give This Discount**	**Give your friends 70% discount!** Invite your friends to Collage.com, and your friend will get a 70% discount on the next purchase. You will also get a 70% discount! Your Name* Clara Smith Friends Email* csmith@gmail.com **Invite** Have a lot of friends? You can invite up to five people to try Collage.com. Just submit this form once for each friend.

Figure 9: Example of Email/Link Page Received by Each User in Equitable/Altruistic Framing Groups

* Note: I highlight the difference in framing across different test groups using box of red solid line

The emails were sent out on the same day, at the same time, and only once to each customer in the experiment[33]. Each customer was given a week to send referrals to their friends. Once a customer sends out a referral, a 70% discount coupon, which was valid for 30 days, was sent to both the sender and the receiver (the sender would get the discount coupon regardless of the referral outcome, and this is specified in the email). The email implementation gives me very strong control over the randomized field experiment. First, by targeting predefined randomly drawn customers, I can ensure that the randomization procedure is valid. Second, by restricting the treatment to the messages in the email and by keeping the webpage private and only linking to the corresponding email, I can eliminate potential interference across test groups. Finally, by sending the email once, I reduce the possibility of selection bias in repeated trials.

The randomization ensures that the call-to-action in the email is orthogonal to the customers' previous behaviors. Therefore, any difference in the customers' referral decision and outcomes can be solely and directly attributed to the difference in the received call-to-action for initiating the referral process. I observe several outcomes from the experiment. Firstly, I look at a binary indicator of whether a sender sent a referral. Secondly, I look at the total number of referrals sent by senders. Lastly, I check the number of recipients' purchases originated by senders' referrals. The three outcomes are closely inter-related. The first two outcomes characterize the referral behavior, whereas the last outcome characterizes the referral outcome.

[33] As the treatment in the experiment was framed messages sent by email, a small portion of customers (around 7%), who have selected to unsubscribe future email from the company at the time of their previous purchase were excluded in the analysis. The exclusion does not affect our results since the involved customers are minimal and the randomization is orthogonal to the subscription.

3. Empirical Strategy

To identify the effect of different calls-to-action on senders' referral behavior and referral outcomes, I run regression models at the sender level with and without controls. First, I relate the outcome variables to dummy indicators of each of the treatment groups and employ linear probability models and ordinary least squares (Equation 5). The main estimation equation for sender *i* is

$$Y_i = \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \varepsilon_i \quad (5)$$

where Y_i is the outcome variable of the interest (e.g. *sender's decision to share, total number of referrals, number of recipient's purchase that originated from the sender)*.

Additionally, for efficiency purposes and to examine the effects of interesting covariates related to customer affinity (i.e. NPS score and past purchase behavior) and timing of call-to-action (i.e. elapsed time since last purchase), I augment the field experiment data with survey and archival data and employ linear probability models and ordinary least squares (Equation 6).

$$\begin{aligned} Y_i = {} & \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \\ & \beta_4 \times Survey_i + \beta_5 \times NPS_i + \beta_6 \times WeeksSinceLastPurchase_i + \\ & \beta_{numpurchase,category\ k} \times NumPurchase_{category\ k\ i} + \beta_{spending\ category\ k} \times Spending_{category\ k_i} \\ & + \beta_{dailydeal\ category\ k} \times DailyDealPurchase_{category\ k_i} + \varepsilon_i \end{aligned} \quad (6)$$

In the above model, NPS_i indicates the reported NPS score of each sender *i*. The collaborating platform conduct surveys to collect NPS score (intention of spreading word-of-mouth) of the customer after each purchase. While NPS score is widely adopted in practice, there have been only few investigations examining the relationship between

NPS score and actual referral behavior (Keiningham, Cooil, Aksoy, Andreassen, and Weiner 2007). The data of NPS scores collected prior to the experiment allow me to estimate the main effect as well as the moderator effect of NPS score on the referral behaviors and outcomes. In the experiment, 23% of the users had reported their NPS score prior to the experiment. I also include a survey response dummy variable (e.g. $Survey_i$) as a control, which would account for situations when NPS score information is missing.

In addition, I measure the recency of a sender's purchase using $WeeksSinceLastPurchase_i$, i.e. the number of weeks that have elapsed between the sender i's last purchase and the day of the experiment. The lower the value of $WeeksSinceLastPurchase_i$, the more recent the sender's last purchase is. As discussed in hypothesis 2B, I am interested in the moderator effect of the variable -- how the effect of a call for a referral campaign on senders' referral behavior changes over time after the purchase. As the timing of the experiment was exogenous to the recency of senders' last purchase, the coefficient of $WeeksSinceLastPurchase_i$ variable captures this dynamic effect. Despite the anecdotal evidence indicating that user's response to the referral campaign changes over time, this dynamic property of response to referral program has received less attention in the prior research. Lastly, I also control for sender's behavior prior to the experiment, including purchase characteristics such as number of past purchases (e.g. $NumPurchase_i$), amount of money paid (e.g. $Spending_i$), discount received (e.g. $Discount_i$), and daily deal channel used (e.g. $DailydealPurchase_i$) across different product categories *k* (e.g. *Blanket, Photobook, Canvas, and others*)[34]. To further test how different customer characteristics moderate the effect of call-to-action, I interact the moderating variables with the test group indicator and estimate the model using the following specification

$$Y_i = \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \beta_{Moderator\_egoistic} \times Treatment\_egoistic_i \times Moderating\_var_i + \beta_{Moderator\_equitable} \times Treatment\_equitable_i \times Moderating\_var_i + \beta_{Moderator\_altruistic} \times Treatment\_atruistic_i \times Moderating\_var_i + \beta \times Control\_var_i + \varepsilon_i \quad (7)$$

where $Moderating\_var_i$ denotes different moderating variables such as sender's past purchase behavior, NPS score, and the recency of sender's last purchase and where $Control\_var_i$ denotes all the control variables used in equation 6.

4. Results

Before reporting the results of the analysis, I compare the differences in customers' characteristics across the four test groups to ensure that the randomization is at work. Table 13 demonstrates that the sample is well balanced across all the covariates, supporting the validity of the randomization procedure.

Testgroup	Sample size	Total number of past purchases		Total spending		Week after the last purchase		Using dailydeal (DV)		Response to survey(DV)	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
C	9186	1.4402	0.9925	83.2190	120.2924	11.6090	3.3566	0.4526	0.4978	0.2296	0.4206
T1 (Egoistic)	27919	1.4330	0.9742	84.2600	117.6745	11.6880	3.3327	0.4479	0.4973	0.2292	0.4203
T2 (Equitable)	28113	1.4395	1.0300	84.5204	107.2044	11.6934	3.3353	0.4495	0.4975	0.2276	0.4193
T3 (Altruistic)	27929	1.4393	1.4870	84.4201	110.0156	11.6730	3.3371	0.4501	0.4975	0.2321	0.4222
p value for joint test		0.8950		0.8042		0.1842		0.8752		0.6428	

Table 13: Randomization check

[34] Table 31 outline the descriptive statistics of the customers in the study

4.1 Main Results

I first report the main effect of different calls-to-action on the three outcomes of interest (customer's referral decision, total number of referrals and number of recipient's purchase) in Table 14. The results of linear probability model in column (1) show that, relative to the control group, only the altruistic framing significantly increases the probability of a sender making any referrals. The increase is more than 60% over that of the control group. The effect of altruistic framing is also significantly higher than the effect of egoistic framing (T3-T1) by 113% and equitable framing (T3-T2) by 29%. When examining the effect of call-to-action on the total number of referrals, I find that both equitable and altruistic framing significantly increase the total number of referrals compared to the control group by 43% and 86%, respectively (Table 14, column (3)). Again, the effect of altruistic framing on the total number of referrals is 99% higher than the effect of egoistic framing (T3-T1) and 30% higher than the effect of equitable framing (T3-T2). Hence, H1A is strongly supported.

I further present the effect of different calls-to-action on the referral outcomes in Table 14 column (5). I find that altruistic framing leads to significantly larger number of recipients' purchases (by 245%) compared to the control group. A comparison between altruistic framing and other framing effects shows that altruistic framing leads to a significantly higher number of recipients' purchases compared to both egoistic framing (T3-T1) by 425% and equitable framing (T3-T2) by 135%. All the impacts are statistically significant and economically sizable. Therefore, H1B is supported. In addition, I find that the conversion rate (= total number of success referrals / total number of referrals) of the altruistic group is 85% higher than the conversion rate of the control group, and 164% and 81% higher than the conversion rate of egoistic group and equitable group, respectively (Table 15). The results are aligned with the fact that selective sharing driven by altruistic considerations (of friends' payoff) may result in a higher conversion rate (Aral et al. 2011) and thus are more effective.

DV	Referral decision		Total number of referrals		Number of recipients' purchase	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0060*** (0.0009)	0.0108*** (0.0016)	0.0083*** (0.0017)	0.0179*** (0.0031)	0.0002 (0.0003)	0.0014*** (0.0005)
T1 (Egoistic)	-0.0015 (0.0010)	-0.0014 (0.0010)	-0.0005 (0.0020)	-0.0004 (0.0020)	-0.0001 (0.0003)	-0.0002 (0.0003)
T2 (Equitable)	0.0014 (0.0010)	0.0015 (0.0010)	0.0036* (0.0020)	0.0037* (0.0020)	0.0001 (0.0003)	0.0000 (0.0003)
T3 (Altruistic)	0.0036*** (0.0010)	0.0036*** (0.0010)	0.0071*** (0.0020)	0.0072*** (0.0020)	0.0005* (0.0003)	0.0005* (0.0003)
Survey	-	-0.0019 (0.0030)	-	-0.0061 (0.0060)	-	-0.0003 (0.0009)
NPS	-	0.0011*** (0.0003)	-	0.0022*** (0.0006)	-	0.0001 (0.0001)
WeeksSinceLastPurchase	-	-0.0012*** (0.0001)	-	-0.0022*** (0.0002)	-	-0.0002*** (0.0000)
NumPurchase_Blanket	-	0.0030*** (0.0008)	-	0.0084* (0.0015)	-	1.28E-05 (0.0002)
Spending_Blanket	-	3.32E-06 (0.0000)	-	1.47E-05 (0.0000)	-	8.22E-07 (0.0000)
Discount_Blanket	-	0.0071*** (0.0016)	-	0.0056* (0.0033)	-	0.0012** (0.0005)
DailydealPurchase_ Blanket	-	-0.0018*** (0.0006)	-	-0.0031*** (0.0011)	-	-0.0004** (0.0002)
NumPurchase_ Photobook	-	0.0104*** (0.0019)	-	0.0159*** (0.0037)	-	0.0016*** (0.0006)
Spending_Photobook	-	-0.0001** (0.0000)	-	-0.0001** (0.0000)	-	-1.3E-05* (0.0000)
Discount_Photobook	-	0.0036 (0.0026)	-	0.0084 (0.0053)	-	0.0004 (0.0008)
DailydealPurchase_ Photobook	-	-0.0094*** (0.0016)	-	-0.0154*** (0.0032)	-	-0.0015*** (0.0005)
NumPurchase_Canvas	-	0.0016 (0.0016)	-	0.0072** (0.0032)	-	5.11E-05 (0.0005)
Spending_Canvas	-	-5.3E-05*** (0.0000)	-	3.55E-05 (0.0000)	-	9.17E-06** (0.0000)
Discount_Canvas	-	0.0044* (0.0024)	-	0.0022 (0.0049)	-	-0.0002 (0.0008)
DailydealPurchase_ Canvas	-	-0.0024* (0.0013)	-	-0.0070*** (0.0027)	-	-0.0002 (0.0004)
NumPurchase_Others	-	0.0026*** (0.0006)	-	0.0029** (0.0012)	-	0.0009*** (0.0002)
Spending_Others	-	-1.9E-06 (0.0000)	-	2.8E-06 (0.0000)	-	-1.4E-06 (0.0000)
Discount_Others	-	0.0083*** (0.0014)	-	0.0142*** (0.0029)	-	6.4E-05 (0.0004)

DailydealPurchase_ Others	-	-0.0030*** (0.0006)	-	-0.0037*** (0.0012)	-	-0.0007*** (0.0002)
p-value (T3 – T1)	<.0001	<.0001	<.0001	<.0001	0.0028	0.0028
p-value (T3 – T2)	0.0026	0.0029	0.0123	0.0138	0.0338	0.0325
Observations	93147	93147	93147	93147	93147	93147
R-squared	0.0006	0.008	0.0004	0.0067	0.0001	0.0013

Table 14: Main Effect

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses.

Testgroup	Conversion rate (%)
Control	2.632
T1 (Egoistic)	1.852
T2 (Equitable)	2.695
T3 (Altruistic)	4.884

Table 15 : Conversion Rate of Each Group

Note: Conversion rate (= total number of success referrals / total number of referrals)

I also report the results of the impact of control variables in Table 14 (Column 2, 4, 6). In addition to the main effects, I control for senders' NPS score, senders' past purchase behavior across different product types, as well as the recency of senders' purchase, as measured by elapsed time between the call for referral and senders' last purchase. As shown in the table, the coefficient of NPS score is significantly positive with regard to referral behavior, i.e. customers with high NPS score are significantly more likely to respond to the campaign and make referrals. This effect is consistent with previous literature (Keiningham et al. 2007). Similarly, the coefficient of $WeeksSinceLastPurchase_i$, elapsed time between senders' last purchase and the referral campaign, is significantly negative with regard to all the outcome variables. As the treatment assignment was exogenous to the recency of senders' last purchase, the variable captures how the effect of call for referral campaign on senders' referral behavior and outcomes decrease over time after their last purchase. The result suggests that the best time for firms to engage customers with a call for referral is immediately after customers' purchases. Finally, I estimate the model using alternative specifications to ensure the results are robust. As can be seen in Appendix D Table 32, I find that the results are consistent across binary outcome models (probit and logit models) and count models (Poisson and Negative Binomial models).

In summary, I find that framing the same incentive scheme differently can significantly affect the effect of call-to-action on customers' referral behaviors and outcomes. I find that the altruistic call-to-action is most effective in driving referral behavior (likelihood of making referrals and the total number of referrals), and results in the best referral outcomes. Moreover, while egoistic framing and equitable framing are widely adopted practice, I find the effect of altruistic framing is significantly higher than the effect of those two types of calls-to-action. Such finding is provocative for both theory and practice. It implies that firms should adopt the altruistic framing in their call-to-action. And it also indicates that altruism may play an important role in online referrals.

4.2 Testing the Role of Altruism using Moderator Effects

Having identified the effectiveness of altruistic framing in driving referrals, I further examine the role of altruism through a variety of moderator effect analysis. Specifically, I test whether the effect of altruistic framing varies based on customer characteristics and the timing of the call-to-action, as articulated in Hypothesis 2A and 2B. As I posit, I should see the higher impact of altruistic framing for customers with high affinity of the product, as customers will care more about their friend's utility and in this case, customers will project their own evaluation onto others (Cronbach, 1955; Ichheiser, 1946). For a similar reason, if altruism is an important driver of online referrals, I should expect the effect of altruistic framing on referral behavior may decrease fast over time as such referral behavior is relying on customers' intrinsic delight/altruism about the product, which may decay over time after their purchase.

I represent customers' affinity with the product by measuring their degree of repeat purchases (Hoyer, 1984) and by their reported NPS score (Reichheld 1996). Therefore, I examine the moderating effects of repeat purchases and NPS score on the treatment effect of different calls-to-action. Using archival data on individual purchase history on the platform, I construct a binary indicator $RepeatPurchases_i$ which indicates whether a sender made more than two purchases in the past, and interact the variable with the treatment group indicator as specified in Equation 7. I report the results in Table 16. I find that the effect of altruistic framing on referral behavior is significantly higher for customers who made repeat purchases. Using the same specification, I examine the moderating effect of NPS score (Table 17) and find that the reported NPS score of a customer positively moderates the effect of altruistic framing on their referral behavior. Customers with a high NPS score are significantly (~73%) more likely to share when they are targeted with an altruistic framing call-to-action. Overall, the results support H2A and are aligned with the theorizing that altruism plays an important role in driving referrals.

DV	Total number of referrals
RepeatPurchases	-0.0139*** (0.0041)
RepeatPurchases * T1(Egoistic)	0.0051 (0.0045)
RepeatPurchases * T2(Equitable)	0.0062 (0.0045)
RepeatPurchases * T3(Altruistic)	0.0102** (0.0045)

Table 16: Moderating Effects of Repeat Purchases

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses. A full set of controls has been applied. Variable 'RepeatPurchases' indicates whether a user purchased a product more than twice in the past

DV	Total number of referrals
NPS	0.0017** (0.0008)
NPS * T1(Egoistic)	0.0002 (0.0005)
NPS * T2(Equitable)	0.0003 (0.0005)
NPS * T3(Altruistic)	0.0013** (0.0005)

Table 17: Moderating Effects of NPS Score

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses. A full set of controls has been applied.

I further explore the role of timing of call-to-action in moderating the treatment effect. As mentioned earlier, I expect that the effect of altruistic framing on referral behavior may decrease as more time passes between the customers' last purchase and the call-to-action. This would be consistent with decay in enthusiasm or delight after purchasing the product. I present the moderating effect of the recency of customer's purchase in Table 18. I find that the effect of referral campaign on customers' referral behavior decreases over time (the coefficient of "WeeksSinceLastPurchase" is negative).

More interestingly and consistent with my theoretical prediction, I find that the recency of customers' purchases positively moderates the effect of altruistic framing on the number of referrals. This result supports H2B and helps further triangulate the main story that centers on the fact that the altruistic framing activates users with high product affinity which may lead to more effective referrals. Practically speaking, the analysis suggests that firms should target high affinity customers first in their referral campaigns, and that the best time to initiate call-to-action is immediately after purchase, when customers are most enthusiastic about the product.

DV	Total number of referrals
WeeksSinceLastPurchase	-0.0018*** (0.0005)
WeeksSinceLastPurchase * T1(Egoistic)	0.0006 (0.0006)
WeeksSinceLastPurchase * T2(Equitable)	-0.0007 (0.0006)
WeeksSinceLastPurchase * T3(Altruistic)	-0.0012** (0.0006)

Table 18: Moderating Effects of Timing

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses. A full set of controls has been applied. Variable 'WeeksSinceLastPurchase' indicates the recency of a sender's purchase, as measured by the number of weeks that have elapsed between the sender's last purchase and the day of the experiment. Therefore, the lower the value, the more recent the sender's last purchase is. Negative sign of 'WeeksSince LastPurchase' indicates positive moderating effect of the recency of a sender's purchase

4.3 Post-experiment Survey on Referral Motives

To further investigate the underlying mechanisms explaining the main result, I conducted a post-experiment survey designed to shed light on customers' motives for sharing or not-sharing the referrals. The survey was administered three weeks after the experiment to all the 100,000 customers in the experiment, including those who shared and didn't share.

Figure 10 describes the survey sent to each customer (with the questions and choices). The survey allows me to perform a direct test of Hypothesis 3. In addition, the survey helps me conduct a manipulation check, namely, whether a given framing (e.g. emphasizing altruism) provokes customers with the corresponding motive (e.g. altruism). It permits me to measure the impact of different framing on customers' motive to share or not to share, and to understand how different motives connect to customers' referral decisions and the outcomes.

Survey to non-sharer

Why didn't you share the promo code (70%) with your friends/family? Please check ALL that apply.

- I am not satisfied with previous purchase(s)
- The incentive offered is not good enough to justify sharing
- I cannot think of a friend or family member who might like collage products.
- I feel guilty or uneasy about using referral incentive programs
- It's time consuming and costly for me to share referrals

Survey to sharer

Why did you share the promo code (70%) with your friends/family? Please check ALL that apply.

- I am highly satisfied with previous purchase(s)
- I am happy with the promotion that I get when making referral(s)
- I have family/friend(s) who might like the collage products
- I have family/friend(s) who might be happy with the promotion

Figure 10. Questionnaire in the Survey

When analyzing the survey responses[35], I find significant differences across the treatment groups as shown in Figure 11 and 12. The left panel in Figure 11 shows the response to the question: "I feel guilty or uneasy about using referral incentive programs". Compared to control group and egoistic group, I find that the portion of the customers reporting guilt as the reason they didn't share is significantly smaller in the altruistic group. The results show that altruistic framing reduces sender's guilt from getting a reward for the referral. The results from the survey together with the empirical

[35] The survey had 785 valid questionnaires returned, representing a response rate of 0.8%

findings suggest that guilt may be an important motive for customers not to share. Therefore, when designing the referral program, firms may benefit from using the altruistic framing to reduce the feeling of guilt in customers in order to increase their referrals.

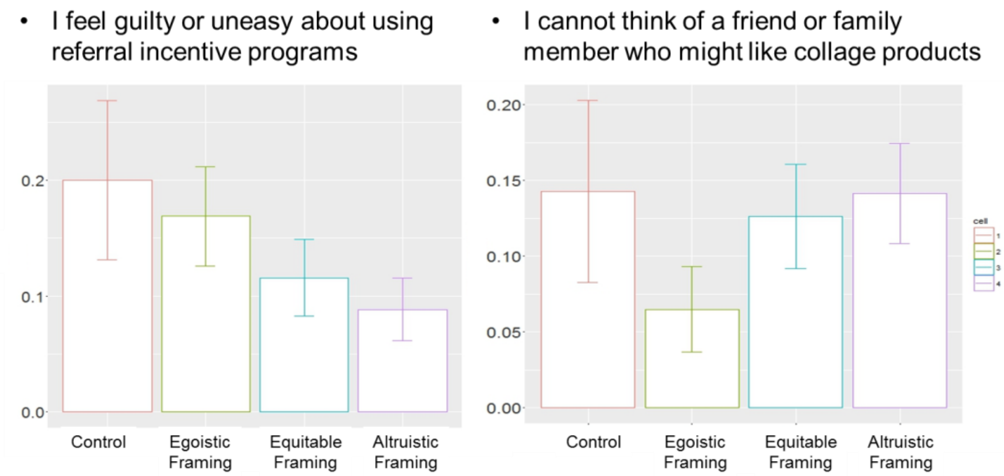


Figure 11: Response of Motives Not to Share

The right panel in Figure 11 (responses of users who did not share) shows the response to the question: “I cannot think of a friend or family member who might like collage products”. On one hand, I hypothesized that altruistic framing enhance senders’ care for their friends and thus, make it harder for them to find potential recipients. However, Figure 11 indicates that altruistic framing doesn’t increase the difficulty for the sender to identify a potential recipient compared to control group. Interestingly, when compared to those who receive egoistic framing, the customers who receive altruistic framing are significantly more likely to report “higher difficulty” in identifying friends or family as the recipient. The contrast reflects how different framing primes the customers to think differently: egoistic framing enhances sender’s focus on one’s own benefits, while altruistic framing does the opposite, putting the senders' focus who else would benefit the most.

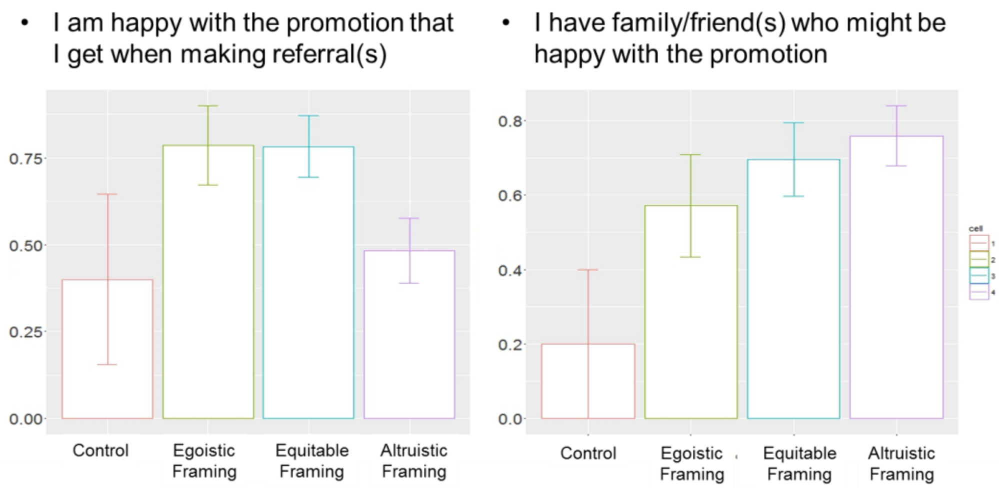


Figure 12: Responses of Motives to Share

Next, Figure 12 displays treatment effect differences observed in users who chose to share the online referral. The left panel exhibits the response to the question: "I am happy with the promotion (70% discount) that I get when making referral(s)". Aligned with the above argument, the figure shows that compared to the control group and the altruistic group, more customers in the egoistic group and equitable group shared because of the reward for themselves. The right-panel in Figure 12 shows the response to the question: "I have family/friend(s) who might be happy with the promotion (70% discount)." The figure shows that compared to the control group, a significantly larger number of senders in the altruistic group made referrals because of their care about others' benefits. The two panels in Figure 12 show that different ways of framing messages impacts the different motives of senders to share. Customers are more likely to report motive (e.g. altruism) that corresponds to the framing they received (e.g. altruistic framing). In addition, the results provide further evidence that customers who received altruistic framing care more about their friends' utility, and are thus able to generate more effective referrals, which in turn, explains the highest conversion rate of altruistic framing across all test groups.

Overall, the results from the survey support H3 as well as allow me to look into the effect of different framing on referral behaviors and outcomes. Firstly, I establish that a significant difference in customers' motive consistent with the treatment confirms that the manipulation was successful. Secondly, the survey results align nicely to explain the impact of different framing with regards to its effect on different customers' motives. The results show that altruistic framing reduces senders' guilt and enhances altruism; whereas egoistic framing enhances concern about one's own welfare but doesn't reduce guilt. Finally, the results show how altruistic framing positively affects both referral decisions and the subsequent outcomes through different mechanisms. On the one hand, altruistic framing increases senders' probability to share by reducing their guilt from getting referral rewards. On the other hand, altruistic framing improves referral outcomes by enhancing the altruistic feeling and by encouraging selective and better-targeted referrals.

5. Discussion

In this essay, I design and conduct a randomized field experiment that allows me to examine this question and make causal inference. Specifically, I collaborate with an e-commerce platform and target 100,000 customers in different groups with emails that only vary in their call-to-action for initiating the referral process. The design allows me to reduce the risk of various challenges of experimental analysis such as: the validity of the randomization procedure, the likelihood of interference and the possibility of selection bias across groups. I find that the altruistic framing of the call-to-action is most effective in driving more referrals and better outcomes.

The findings have both theoretical and practical implications that are linked to my hypotheses. First, this is the first study to show that altruism is an important driver underlying the success of online referrals. I find that altruistic framing positively affects both referral decision and outcomes through multiple mechanisms. Specifically, altruistic framing can improve the referral process by reducing senders' guilt from getting referral rewards and by encouraging better targeting by senders which may lead to higher conversion rate. The results together provide concrete and causal support to the hitherto under-studied role of altruism in creating social contagion. This essay is also among the first to provide comprehensive (direct and indirect) evidence on the underlying motives that drive or discourage senders' online word-of-mouth. Such insights on the motives of people who chose to refer others to products or services may serve as guiding principles for firms that wish to encourage word-of-mouth.

Additionally, this essay also closes the gap in the literature around the optimal design of referral programs. While previous research has investigated the design of the message from sender to the recipients (Sun et al. 2014), no study has investigated how firms can optimally design the call-to-action to engage customers in initiating referrals in the first place. I contribute to the literature by examining how firms can optimally frame a call-to-action, keeping every other aspect, namely the incentive split and the recipients' message, constant across treatments. The results show that altruistic call-to-action for referral leads to higher likelihood of referral and better referral outcomes. In addition, the effect of altruistic framing is significantly higher than the effect of egoistic framing and equitable framing for a variety of the sharing outcomes. Therefore, companies which seek to maximize returns from their referral programs should use altruistic framing in their call-to-action for referral. In addition, I find that this altruistic framing is more effective for users who have made repeat purchases, for those who reported a higher NPS score and for those just purchased. Thus, firm should target loyal customers soon after their purchases in the referral campaigns.

Conclusion

Firms increasingly rely on digital word-of-mouth to increase their customer base and product sales. Given the existing knowledge on the effect of message design, it is important to understand the effect of different incentive and calls-to-action design on customers' referral behavior and outcome. In my dissertation, I examine whether and how a firm can enhance the effectiveness of a referral program by varying incentives and messages shared by customers with their friends using two large-scale randomized field experiments. In the first essay, I found that that the generous pro-social referral reward schemes dominate purely selfish schemes in creating word-of-mouth. In the second essay, I show that 'altruistic' call for referral is most effective in driving sharing behavior and result in better sharing outcomes. All the results together provide direct managerial implications for firms to optimally design the referral program and support that altruism plays an important role in referral behavior.

This dissertation complements three streams of prior research at the intersection of information systems and marketing: estimating causal peer influence in social networks, constructing optimal referral design to promote WOM based adoption, and exploring the underlying motives of referral behavior. Although previous studies using randomization trials have demonstrated peer influence at work (Aral and Walker 2011b, Bapna and Umyarov 2016), there hasn't been much empirical investigation to discover how different referral incentive schemes and call-to-action drive the peer influence in the social contagion process. Existing studies of designing referral programs on WOM mainly focused on senders' behavior and rarely considered incentive sharing schemes or different message design (Kornish and Li 2010, Wirtz and Chew 2002, Ryu and Feick 2007). I contribute to the literature by studying how firms can optimally design the incentive and message to the sender (call-to-action) to engage customers. Finally, my study is also among the first to show that altruism is an important driver of information sharing among customers and how such motive leads to sharing decision and sharing outcomes (Dunn and Norton 2013, Bitzer et al. 2007, Anderson and Agarwal 2011, Jabr et al. 2014, Xia, et al. 2012).

This dissertation also provides several opportunities for further research. In the first essay, one aspect that this trial was not aimed to uncover was the exact psychological reasons behind the user's referral behavior, but to study which of the referral incentive scheme works best for maximizing word-of-mouth based adoption. However, results, especially from Study 1, showing the efficacy of the generous scheme hint at the possible role of happiness from pro-social behavior in creating diffusion in social networks. Similarly, the failure of the selfish reward scheme hint at the potential role of guilt felt by users in benefitting from inviting their friends. Studying these exact psychological motivations of users may be considered in future works, which would require designing a different set of experiments in which the incentives only influence one possible motivation at a time while controlling for all the others.

Additionally, given that I observed differences between the referral behavior of the existing and the new users in the trial, I expect future research to examine whether the referral reward structure offered to a user needs to evolve over time. This begs several questions: (i) How should firms dynamically adapt the design of the referral incentive scheme to maximize adoption (*e.g.*, optimally switch over from selfish or split reward scheme to a generous reward scheme based on how long a user has been using the product)? (ii) Does this behavior hold more generally for contexts beyond those considered in this paper?

Regarding the second essay, a logical next step is for researchers to examine the integration of two different types of widely used calls-to-action., namely call for referral and call for purchase. Specifically, customers may play two roles in their lifecycle: purchaser and influencer, and firms may engage customers with either call for referral or call for purchase at different points in time. However, there is a fundamental tradeoff between the two calls due to the limited attention of customers. Similar to a call for purchase, a call for referral is usually sent out to customers in the form of digital marketing communication, e.g. through electronic email and mobile messages. Given the limited bandwidth of marketing communication, it is important and interesting to compare call for referral with call for purchase, especially promotional advertising, which is the dominant form of marketing communication from a firm. Based on the results from the experiment, I identify three types of differences between the two forms of communication. First, for durable goods like printed products I studied in this paper, calls for purchase are, in general, not effective immediately after purchase. However, the results provide evidence that this may be the best time to engage customers with referral marketing. Second, promotional email is more effective when targeted to less loyal customers in calls for purchase. However, in calls for referral, promotional email highlighting the reward to a friend is most effective for loyal customers because of altruism. Finally, while calls for purchase are always highlighting customer's own benefits, the optimal design for calls for referral should highlight the benefits for their friends. Interestingly, all the three differences, the timing, the targeting and the design make an altruistic call-to-action for referral complementary with the call for purchase in marketing communication. Thus firms can optimally combine them to form an integrated communication strategy and engage customers throughout their lifecycle. Although both marketing communications are widely used in practice, there have been no empirical tests comparing performance of these two calls-to-action when they are used together. I expect future studies to deepen our understanding by providing guidelines how firms can optimally integrate these two calls-to-action.

In addition, in the second essay, I test the importance of altruism by varying the framing of call-to-action for the same equal-split incentive scheme. Thus, even under the altruistic framing, the sender may still gain monetary reward from making referral rewards. Given the good performance of altruistic framing, it might be interesting for future research to determine whether altruism is strong enough to make the reward to the sender redundant. In other words, will the sender still be willing to make referrals even without reward to herself?

Understanding which type of incentive scheme and call for referral are most effective in creating social contagion through word-of-mouth is a crucial step in developing optimal referral marketing strategies. I believe that my dissertation, through two large-scale randomized field experiments, can contribute to the rich literature in IS and marketing on word-of-mouth and social contagion by providing insights on the effect and mechanisms of different incentive structure and calls-to-action for WOM referrals.

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Appendix A

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0034	0.0145	-0.23	0.8161
T0	0.0013	0.0018	0.72	0.4708
T1	0.0010	0.0018	0.57	0.5716
T2	0.0035	0.0018	1.94	0.052
T3	0.0077	0.0018	4.37	<.0001
Game_count_(t-1)	-0.0162	0.0015	-11.2	<.0001

Table 19. Effect of Incentive Schemes on Number of Invites with Lagged Game Count

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0003	0.0121	-0.02	0.9807
T0	0.0014	0.0015	0.91	0.3638
T1	-0.0008	0.0015	-0.55	0.5807
T2	0.0025	0.0015	1.67	0.0949
T3	0.0034	0.0015	2.3	0.0215
Game_total_player	0.0414	0.0003	123.88	<.0001

Table 20. Effect of Incentive Schemes on Number of Invites with Total Number of Players in a game

Variable	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.0031	0.0145	-0.21	0.831
T0	0.0039	0.0045	0.87	0.3848
T1	0.0077	0.0048	1.6	0.1104
T2	0.0067	0.0049	1.38	0.1665
T3	0.0167	0.0044	3.8	0.0001
T0*NewUser	0.0012	0.0019	0.63	0.5299
T1*NewUser	0.0004	0.0019	0.23	0.8184
T2*NewUser	0.0033	0.0019	1.75	0.0796
T3*NewUser	0.0066	0.0019	3.55	0.0004
Game_count_(t-1)	-0.0163	0.0015	-11.24	<.0001

Table 21. Effect of Incentive Schemes on Number of Invites for New and Existing Users

Variable	Group	Est.	SE	t-value (C vs. T)	p-value	F-value	Pr>F
login_days	C	2.4706	0.7332			1.44	0.2233
	T0	1.9286	0.2490	0.89	0.3746		
	T1	1.6765	0.1726	1.40	0.1690		
	T2	1.8611	0.2647	0.97	0.3387		
	T3	2.5789	0.3931	-0.14	0.8878		
login_hours	C	3.4118	1.2219			2.11	0.0822
	T0	2.6667	0.4279	0.73	0.4692		
	T1	2.2941	0.3469	1.13	0.2631		
	T2	2.7500	0.4918	0.60	0.5496		
	T3	4.3421	0.7129	-0.69	0.4911		
game_count	C	0.5882	0.3436			0.7	0.5962
	T0	1.4048	0.6791	-0.75	0.4587		
	T1	0.9706	0.5196	-0.49	0.6248		
	T2	0.8056	0.3305	-0.40	0.6873		
	T3	1.9474	0.8053	-1.10	0.2747		
game_total_player	C	2.6471	1.4974			0.6	0.6603
	T0	4.9286	2.3940	-0.59	0.5606		
	T1	3.3235	1.6524	-0.26	0.7936		
	T2	3.0556	1.2755	-0.19	0.8483		
	T3	6.6316	2.5372	-1.01	0.3164		
game_ave_player	C	4.7000	0.7000			0.29	0.8834
	T0	3.3981	0.1628	2.74	0.0227		
	T1	3.8750	0.4820	0.98	0.3594		
	T2	3.7270	0.4027	1.28	0.2373		
	T3	3.7583	0.3576	1.25	0.2379		
game_total_time	C	281.3	154.3			0.38	0.8197
	T0	502.7	245.5	-0.55	0.5819		
	T1	362.6	164.9	-0.32	0.7541		
	T2	325.8	130.0	-0.21	0.8384		
	T3	578.6	195.9	-0.95	0.3444		
game_ave_time	C	528.9	101.6			0.2	0.9404
	T0	360.1	60.3843	1.45	0.1809		
	T1	464.2	126.5	0.33	0.7518		
	T2	438.1	59.5475	0.81	0.4408		
	T3	402.1	72.1363	0.88	0.3988		
location_count	C	1.2941	0.2539			1.7	0.1533
	T0	1.1905	0.1240	0.41	0.6831		
	T1	1.0294	0.1367	1.01	0.3197		
	T2	1.2222	0.1443	0.26	0.7930		
	T3	1.5789	0.1946	-0.84	0.4021		

Adoption_count	C	0.1176	0.1176			0.23	0.9201
	T0	0.1429	0.0874	-0.16	0.8726		
	T1	0.1765	0.1299	-0.29	0.7723		
	T2	0.0556	0.0387	0.63	0.5291		
	T3	0.1842	0.1404	-0.30	0.7684		
app_update_date	C	10.9412	2.4933			1.71	0.1497
	T0	12.0238	1.9250	-0.32	0.7528		
	T1	10.5000	2.1120	0.13	0.8994		
	T2	14.3611	2.3167	-0.90	0.3709		
	T3	6.7632	1.4994	1.50	0.1404		
Join_time_duration	C	61.7622	2.0697			0.44	0.7806
	T0	60.0292	1.2203	0.58	0.4448		
	T1	59.3829	1.0777	1.27	0.2604		
	T2	59.1250	1.2404	1.32	0.2505		
	T3	59.6310	1.1742	0.92	0.3383		

Table 22 Pairwise Comparison of the Pre-treatment Behavior across Control and Treatment for Existing Users

Appendix B

As user's attachment and usage of the product and mechanisms that govern contagion processes in networks changes over time (Aral et al. 2009, Aral and Walker 2011b), I therefore expect that the effect of incentive scheme on sender's behavior would also change over time. If so, understanding the factors that influence the sender's behavior over time is an important component of the design of successful referral programs. Therefore, I conduct a secondary analysis to understand the underlying mechanisms of the observed effects. Specifically, I examined heterogeneity in the treatment effect around the time the user joined the site. Table 23 outlines the statistics of user activity during the experiment period with t-tests for the statistical significance of differences between the existing users (users who joined the site before the treatment) and new users (users who joined the site during the treatment) [36].

Existing user*	**Variable**	**Est.**	**SE**	**t-value**	**p-value**
0	login_days	1.2190	0.0148	0.09	0.9308
1	login_days	1.2143	0.0948		
0	login_hours	1.5013	0.0341	-1.98	0.0482
1	login_hours	1.7440	0.2019		
0	game_count	0.1760	0.0371	-2.47	0.0136
1	game_count	0.4702	0.1223		
0	game_total_player	0.6232	0.1297	-2.97	0.0030
1	game_total_player	1.8631	0.4359		
0	game_ave_player	3.5241	0.0817	-3.68	0.0004
1	game_ave_player	4.2212	0.2217		

[36] The new and existing users are not significantly different in terms of their *login_days* (number of days a user logged into the game) and *location_count* (number of unique locations a user played at), which suggests that the differences may not driven by demographic factors or intrinsic user characteristics (location, availability, interest), but because of differences in invitation behavior and resulting game engagements. Hence, I study the heterogeneous effects of incentive schemes with respect to the experience of the user, measured in terms of the duration over which the user has been using the application.

0	game_total_time	61.6173	12.9886	-3.52	0.0004
1	game_total_time	209.8	46.2597		
0	game_ave_time	382.6	30.6265	-2.53	0.0131
1	game_ave_time	536.7	56.7104		
0	location_count	0.9583	0.0137	0.99	0.3243
1	location_count	0.9107	0.0750		
0	adoption_count	0.0385	0.00705	-2.90	0.0038
1	adoption_count	0.1071	0.0316		
0	join_time_duration	54.1545	0.3071	-42.82	<.0001
1	join_time_duration	111.2	2.8936		

Table 23 Summary Statistics of the Behavior across Existing and New Users

*Note: 1 denotes the group of organic existing user, 0 denotes organic new users

As demonstrated in Table 24, results from this analysis show that there are heterogeneous effects of incentive schemes on referrals with respect to the type of the user. Results of the two-way fixed effects model show that the generous reward increases the number of invited adoptions for both new and existing users, but the treatment effect is higher for new users.

Variable	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	-0.00306	0.0145	-0.21	0.8330
T0	0.003352	0.00445	0.75	0.4518
T1	0.007402	0.00481	1.54	0.1238
T2	0.006498	0.00485	1.34	0.1807
T3	0.0154***	0.00441	3.51	0.0005
T0*NewUser	0.0012	0.00194	0.63	0.5298
T1*NewUser	0.0003	0.00190	0.18	0.8561
T2*NewUser	0.0031	0.00189	1.66	0.0979
T3*NewUser	0.0061***	0.00185	3.32	0.0009

Table 24. Effect of Incentive Schemes on Number of Invites for New and Existing Users

These results together confirm the main findings of the study: different incentive schemes have different effectiveness in promoting offline WOM-based adoption depending on the whether the users are new comers or existing users of the product. Additionally, I found that in this context the generous reward schemes dominates especially for new users.

Appendix C

OLS	DV: *invite_num_sent*			
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	1.2307	0.6355	1.94	0.0556
T1 (Selfish)	1.9615	0.8988	2.18	0.0314
T2 (Split)	0.8077	0.8988	0.9	0.371
T3 (Generous)	0.9692	0.9077	1.07	0.2882

Table 25. Effect of Incentive Schemes on the Number of Referrals

OLS	DV: *invite_num_converted*			
Parameter	**Estimate**	**Standard Error**	**t Value**	**Pr > |t|**
Intercept	0.2692	0.3313	0.81	0.418
T1 (Selfish)	0.8461	0.4685	1.81	0.074
T2 (Split)	0.8846	0.4685	1.89	0.062
T3 (Generous)	0.8908	0.4732	1.88	0.063

Table 26. Effect of Incentive Schemes on the Number of Adoptions

Poisson	DV: *Invite_num_sent*			
Parameter	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	0.6775	0.1381	24.09	<.0001
T1 (Selfish)	0.4399	0.169	6.77	0.0093
T2 (Split)	-0.0186	0.1891	0.01	0.9217
T3 (Generous)	0.1892	0.1794	1.11	0.2915

Table 27. Effect of Incentive Schemes on the Number of Referrals (Poisson)

Poisson	DV: *Invite_num_converted*			
Parameter	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-1.3122	0.378	12.05	0.0005
T1 (Selfish)	1.4214	0.4211	11.39	0.0007
T2 (Split)	1.4553	0.4197	12.02	0.0005
T3 (Generous)	1.4606	0.4211	12.03	0.0005

Table 28. Effect of Incentive Schemes on the Number of Adoptions (Poisson)

Linear probability model	DV: *Decision_to_adopt*			
Parameter	**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	0.235	0.0766	3.07	0.0022
Group 1 (Selfish)	0.0996	0.0911	1.09	0.2739
Group 2 (Split)	0.2568	0.1099	2.34	0.0195
Group 3 (Generous)	0.1908	0.1128	1.69	0.0706
	Clustered errors at sender level			

Table 29. Effect of Incentive Schemes on the Referral Acceptance

Logit	DV: *Decision_to_adopt*			
Parameter	**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	-1.1801	0.426	-2.77	0.0056
T1 (Selfish)	0.4929	0.48	1.03	0.3045
T2 (Split)	1.1474	0.53	2.16	0.0304
T3 (Generous)	0.8813	0.5441	1.62	0.0853

Probit	DV: *Decision_to_adopt*			
Parameter	**Estimate**	**Standard Error**	**Z**	**Pr > |Z|**
Intercept	-0.7224	0.2492	-2.9	0.0038
T1 (Selfish)	0.2953	0.2836	1.04	0.2977
T2 (Split)	0.7019	0.3181	2.21	0.0273
T3 (Generous)	0.5354	0.3266	1.64	0.0912

Table 30 Effect of Incentive Schemes on the Referral Acceptance (Logit/Probit)

Appendix D

Variable	Mean	Median	Std Error	Std Dev
LastPurchaseWeek	11.6773	11.6773	0.0109	3.3372
survey	0.2296	0.0000	0.0014	0.4206
NPS	9.1915	10.0000	0.0122	1.7853
NumPurchase_Blanket	0.7011	1.0000	0.0027	0.8328
Spending_Blanket	48.5692	37.9800	0.2325	70.9464
Discount_Blanket	0.3318	0.4972	0.0010	0.3138
DailydealPurchase_ Blanket	0.2743	0.0000	0.0020	0.6173
NumPurchase_ Photobook	0.1074	0.0000	0.0015	0.4496
Spending_Photobook	3.0357	0.0000	0.0543	16.5807
Discount_Photobook	0.0494	0.0000	0.0006	0.1757
DailydealPurchase_ Photobook	0.0765	0.0000	0.0013	0.3920
NumPurchase_Canvas	0.1518	0.0000	0.0016	0.4881
Spending_Canvas	7.4883	0.0000	0.1091	33.3022
Discount_Canvas	0.0768	0.0000	0.0007	0.2164
DailydealPurchase_ Canvas	0.0991	0.0000	0.0013	0.4049
NumPurchase_Others	0.4773	0.0000	0.0034	1.0302
Spending_Others	25.1908	0.0000	0.2548	77.7624
Discount_Others	0.1922	0.0000	0.0010	0.2929
DailydealPurchase_ Others	0.1744	0.0000	0.0025	0.7651

Table 31. Descriptive Statistics of User Activity

DV	Referral decision		Total number of referrals		Number of recipients' purchase	
	Logit	Probit	Poisson	Negative Binomial	Poisson	Negative Binomial
Intercept	-5.0128*** (0.0467)	-2.4764*** (0.0164)	-4.7947*** (0.1147)	-4.7947*** (0.1616)	-8.4323 (0.7071)	-8.4323 (0.7672)
T1 (Egoistic)	-0.3915*** (0.0787)	-0.1374*** (0.0271)	-0.0671 (0.0020)	-0.0671 (0.1872)	-0.4185 (0.866)	-0.4185 (0.9315)
T2 (Equitable)	0.1186* (0.0678)	0.0408* (0.0241)	0.3619*** (0.1271)	0.3619** (0.1826)	0.3855 (0.7817)	0.3855 (0.8536)
T3 (Altruistic)	0.3722*** (0.0638)	0.1332*** (0.023)	0.6211*** (0.1244)	0.6211*** (0.1809)	1.2394* (0.74)	1.2394* (0.8157)

Table 32. Treatment Effect under Alternative Specifications

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses.