Analyzing the Impact of Incentive Structure on the Diffusion of Mobile Social Games: A Randomized Field Experiment

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Abstract

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. Recent literature (Aral and Walker 2011a, Bapna and Umyarov 2015) has causally established that peer-effects are 'at-work' in the general population of users of 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 using specific mechanisms that may be at work in spreading peer influence. To answer this question, we conduct a randomized filed experiment to examine how one such important mechanism of social contagion – offline word-of-mouth – can be triggered using economic incentives. Our research design involves manipulations of how the monetary reward is shared between the inviter and the invitee of the referral: selfish reward (inviter gets all), equal reward (50-50 split), and generous reward (invitee gets all). The unique context of our experiment, mobile social gaming, allows us to measure *offline WOM* as a driver for the adoption of digital goods. Our results show that in the aggregate general population, the generous pro-social referral reward schemes dominate purely selfish schemes in creating offline word-of-mouth. Further heterogeneity analysis help establish that while the generous reward scheme increases the number of adopters in general, the equal split reward scheme increases the number of adopters only for new users. Selfish reward schemes did not perform well among any user group, which lends support to metaperception theory that predicts that guilt accumulation in social contexts can inhibit referrals. The results can help in designing effective referral reward schemes for viral adoption in the digital world.

Keywords: social contagion, viral marketing, referral incentive design, offline WOM

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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 2011, Bapna and Umyarov 2015) 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 we create, perhaps even maximize, social contagion using specific mechanisms that may be at work in creating social contagion. This is the focus of this paper. In particular, we focus on using economic incentives to maximize offline word-of-mouth as a mechanism for spreading awareness 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), we focus on **offline word-of-mouth** (WOM) partly because we believe that it is an important, possibly dominant[1], social contagion mechanism. It has the additional challenge that it has traditionally been hard to measure as it does not lend itself to digitization. We detail how we overcome this challenge when we present the institutional context of our paper.

The broad category of economic incentives we use fall under the label of what are called referral rewards. A firm typically invites an existing customer to refer and bring in

[1] 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

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 refer new customers[2]. Groupon also offers a user $10 Groupon Bucks[3], 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[4]. 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[5]. 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:

> *"…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'[6]…"*

This begs the design of a systematic study of effectiveness of these different incentive schemes on the offline word-of-mouth. We explored this research question using a

[2] https://www.dropbox.com/referrals
[3] http://www.groupon.com/referral
[4] https://www.lyft.com/help/article/1455280
[5] https://awesomesauceeats.wordpress.com/tag/blue-apron/
[6] Rosen 2009, The Anatomy of Buzz Revisited: Real-life lessons in Word-of-Mouth Marketing, Crown Business.

randomized field experiment set in the context of a mobile social gaming application. Our research design involves manipulations of how the monetary reward is shared between the inviter and the invitee of the referral. The design is motivated by multiple theories from economics and sociology. Our initial motivation 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 essence, 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. We like to think of the last category as the Zen Buddhists, for whom, say $10 to a friend brings the same utility as $10 to themselves. In line with this finding of Andreoni and Miller (2002), we test three different incentive schemes: a) the 'selfish' reward scheme, where the inviter gets the reward, b) the 'split' reward scheme, where the inviter and the invitee split the reward, and c) the 'generous' reward scheme, where the entire reward is given to the invitee. Our 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 inviter will motivate them to invite others, while equity theory encourages an even split in the reward between the inviter and the invitee 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 invitee only.

In this paper, we conduct a randomized field experiment to address this issue, namely, how to structure such incentives (i.e., divide it between the inviter and the invitee) to increase adoption of digital goods, in our case – a mobile social game app, through referrals.

To conduct this experiment, we partnered with a mobile gaming app company prior to their release of a new social gaming app. A key feature of this app is that it is a 'party game' (*e.g.,* digitized board game), which can only be played with co-located users. That is, this app's consumption among players is tied to the underlying socio-physical network structure in which these players are embedded. The context of "social gaming" is in itself of particular interest, not only because of the impressive growth rate of the mobile gaming industry, but also because of the communal consumption environment it offers. This is becoming an increasingly common mode of sharing and enjoying digital goods and services with peers. In future studies, we intend to investigate the efficacy of different referral schemes in non-social settings.

Social gaming has been touted as the future of online gaming because it benefits from the convergence of several IT developments – the backend technologies (such as cloud services) that can now run games at scale, while lean frontend devices provide support for gamification and multi-screen gaming experience. According to Riccardo Zacconi, CEO of King.com: *"As smartphones get better and more consumers are opting to their use mobiles and tablets to access games, their expectation is access anywhere… We are* *seeing this is especially the case with casual social games, which transition well onto the mobile platform*[7]*."*

The communal consumption context in a social game also creates a very interesting opportunity to measure offline WOM as a driver for the adoption of digital goods. This is because the app's design does not provide an online invitation feature; instead it relies on players carrying out offline invitations to friends who gather at the same physical location to play the game. When a new player downloads the app to join a game, the app uses geo-sensing to provide a list of other co-located users, to whom the new player can attribute the invitation to. Of course, new adopters can also discover the game by searching the major app stores, in which case the new user gets the default option to attribute to 'own search.' This unique geo-sensing based attribution of location-enabled mobile computing allows us to directly measure offline word-of-mouth and thereby track the actual adoption outcomes. One limitation of this design is that we do not capture the number of invitations sent out by a player, a metric that prior research has focused on (Aral and Taylor 2011). To the best of our knowledge, offline word-of-mouth has not been adequately measured and therefore causally identified as a mechanism for social contagion in the extant literature.

Evaluating such effects of different referral reward schemes on offline WOM have been difficult so far because peer effects and WOM are typically endogenous (Manski 1993, Van den Bulte and Iyengar 2011) and are difficult to trace or measure. But the design of this attribution ability in this social gaming app allows us to overcome that problem. Additionally, the design of the randomized experiment with different reward structure

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[7] http://www.forbes.com/sites/johngaudiosi/2012/07/31/king-com-ceo-riccardo-zacconi-explains-why-the-future-of-social-gaming-is-multi-screen/

allows for causal interpretation of the treatment effects because it avoids the selection problem inherent in observational data infer peer influence (Aral 2011b).

This work complements two streams of prior research on viral 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 2011, Bapna and Umyarov 2015), 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.

Our main finding in this paper is that at the aggregate population level, pro-social referral incentive schemes, namely the split and generous schemes described above, tend to dominate purely selfish schemes in creating offline word-of-mouth in the context of social games. But on examining the heterogeneous treatment effects among new and existing users[8] of the app, we find that while the generous reward scheme increases the number of adopters for both new and existing users, the equal split reward scheme increases the number of adopters only for new users. The selfish reward scheme fails to significantly increase the number of adopters for both new and existing users. We find this intriguing as it reveals a much-nuanced perspective on the effectiveness of referral design than what is widely practiced today. Not to mention that it also adds to the body of evidence against the purely rational theories of self-maximizing economic agents. In

[8] "New" users are those who joined during the trial phase and "existing" users are those who had joined earlier. Given that the app was a newly launched product with no prior brand history, there is unlikely to be any intrinsic difference between the new and existing users, expect for their time of discovery of the app. But even if these users have any intrinsic differences, randomization in the assignment of the users across the different treatment groups, along with a mixed effect model, will allow us to identify and compare the outcomes of the different incentive schemes (treatments).

particular, our results against the efficacy of the selfish scheme for new users hint towards the potential role of guilt in sending out invitations to friends to do something and then benefitting from it – as was alluded to by the Intuit chairman in our quote earlier in this section. But more interestingly, the efficacy of the generous referral scheme for all users shows the existence of pro-social behavior in social networks and lends credence to the theory that user happiness from pro-social spending and actions can dominate egocentrism in the online world. These results have significant implications in the design of viral incentive systems for effective marketing of digital products. It is however worth noting at this stage that while the social gaming nature of this app provides a clean and important context to study the effectiveness of incentive schemes on the offline WOM, it also implies that the generalizability of the results for non-social gaming apps may have to be tested with similar field experiments in the future.

In the next section we review the literature. In Section 3 we provide details of our institutional context. Section 4 outlines our experimental design, and Section 5 presents our empirical approach and results. Section 6 concludes with some directions for future research.

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

2011). 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 2011, Bapna and Umyarov 2015) in online social networks. Aral and Walker (2011) 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 (2015) conduct a randomized filed 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 can we 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 offline 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. Our work 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 inviters 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 in a lab environment. To the best of our knowledge, ours is the first study that reports on the impact of incentive design on the offline WOM-based adoption among real users of a digital good 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 inviter who makes a referral and an invitee (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 inviters 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 our experiment design in which we have explored these three reward-referral mechanisms: selfish reward (inviter gets the whole reward), equal reward (the reward is split equally between the inviter and invitee), and generous reward (invitee 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 invitee. 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 inviter and invitee may be an effective referral mechanism. Lastly, rational choice theory denotes that the reward should be given to an inviter 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 inviter and invitee’s reward amount favors the inviter 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 inviter. Metaperception refers to the process by which people decide based on what others may think of them or their behaviors (Laing, Phillipson, and Lee 1966). According to metaperception theory, in a non-incentivized WOM setting, inviters will perceive themselves as doing a good action and believe that invitees would judge them the way they perceive themselves. However, in an incentivized referral situation in which a referral is rewarded only to the inviter, an inviter might think that the invitee will perceive the referral as being driven by a desire to get the reward rather than 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 paper, we conduct a randomized field experiment to address this issue, namely, how to structure such incentives (i.e., divide it between the inviter and the invitee) to increase adoption of digital goods, in our case – a mobile social game app, through referrals. Our work 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. Institutional Details: Mobile Social Games

We 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 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 our experiment. 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[9]. The aspect of social interactions embedded in the design of these games is also a reason for

[9] http://www.newzoo.com/insights/global-games-market-will-reach-102-9-billion-2017-2/

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, this 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.

Our partner mobile game developing company has created a social game that is intended to be a party game, one that is played in a communal environment. So all the players have to be co-located when they play the game. The application is a multi-player "party" 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 Fig. 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 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.

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 to the game and to help new players explicitly identify their inviters, or attribute the adoption to their own search.

Screenshots:

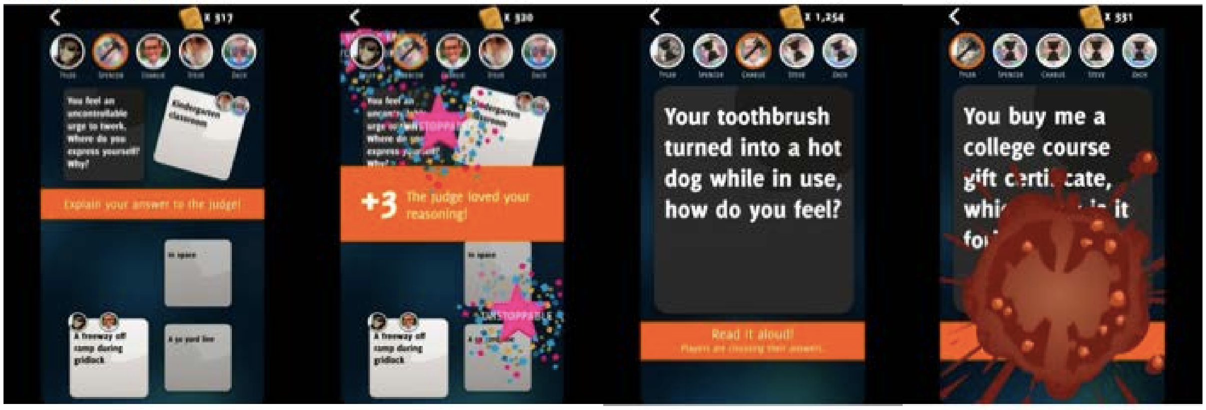

Figure 1: Screenshots of the mobile game app

4. Experimental Design

Our experimental design 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, we designed the randomized field experiment to study which of the three key referral reward structures, namely, selfish (inviter gets the entire incentive), equal sharing (incentive is equally divided), and pro-social (invitee gets the entire incentive), maximizes WOM-based adoption.

Since we partnered with the mobile social gaming company before the release of this app, we were able to record data about two types of users in the trial – "existing users," defined as those who downloaded the app since its release and updated[10] it at the beginning of the experiment period, and "new users" who joined during the experiment

[10] 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.

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 will allow us 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

Group	Control Group (No reward, no reminders)	Test Group 0 – No reward, reminders	Test Group 1 – Selfish reward	Test Group 2– Equal reward	Test Group 3 – Generous reward
Assignment Probability	**0.12**	**0.22**	**0.22**	**0.22**	**0.22**

Table 2: Assignment probability of Experiment Groups

New 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 were test groups defined by their referral reward structure – selfish (inviter gets the entire incentive), equal split (incentive is equally divided), and pro-social (invitee gets the entire incentive)[11]. 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 had no referral rewards but provided users with the reminder notifications. Comparing the previous treatment groups with the fourth group allows us to see (in Section 5.4) that although popular customer pull-back mechanisms, such reminder notifications, are useful in promoting adoptions, the right incentive schemes can have a further 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 we 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.

Next we discuss how the users join the experiment phase of the trial. Our 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. But as shown in Figure 2, users will spend different duration in the experiment depending on when they downloaded or updated the app. But since the assignment is randomized (*i.e.,* nothing in the users past influences the assignment), there is no systematic difference in the time spent in the experiment at a user level in each group. In section 5, using the

[11] While a continuous range of incentive splits of the form (x, 100 – x) between inviter and invitee are possible, we 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.

variable *app_update_date*, we show that there is no significant difference across the control and treatment population of existing users at the beginning of the experiment phase.

When a player joins the experiment, she immediately enters a one-week period, called the *incentivized period,* during which the player can earn the referral reward for inviting new users. When a new user joins a game for the first time, the signup process asks her to identify if she was invited and who her inviter was[12], thus allowing us to explicitly identify any offline WOM-based adoption. The reward received (if any) by the inviter and invitee is based on the group that the inviter belongs to, provided that the inviter is still in the incentivized period. When an invitee attributes the invitation to an inviter, the incentivized period for that inviter resets. However if an invitee attributes an invitation to an inviter when the inviter is no longer in her incentivized period, then no reward is given out for that particular invitation but the incentivized period of the inviter resets. Further invite attributions by new invitees will allow the inviter to continue remain in an active incentivized period.

[12] To facilitate this invite attribution process, the app has a geo-sensing feature that dynamically creates a list of potential inviters from which the invitee can pick the actual inviter. The list includes user A as a potential inviter for a new player, user B, when (1) player A and B begin a match together, i.e., geographically co-located, (2) the match is the first one played by player B, and (3) the match involving players A and B is started within the first hour of player B creating her account. When a new user joins a game for the first time, the signup process asks the player to choose her inviter from the list or explicitly specify her inviter. A user can specify herself as an organic adopter if she discovered it on the app store.

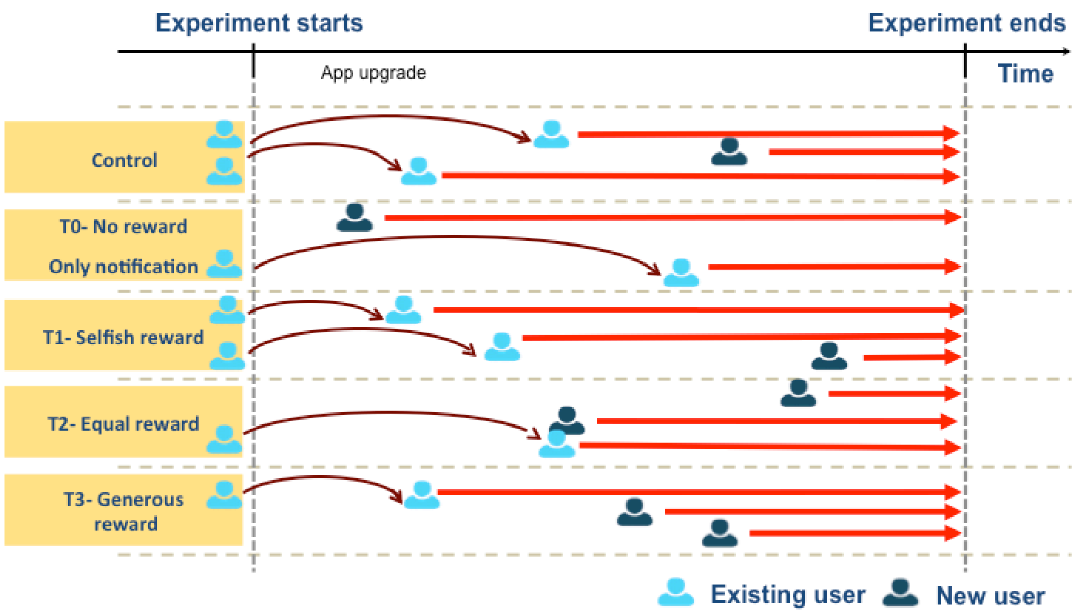

Figure 2: Graphical Representation of How Organic (non-invited) Users Join the Experiment

The referral incentives we offered during the trial were 1000 virtual currency that can be redeemed at any in the app to purchase additional content and cosmetic packs. That is, an inviter in a selfish reward group will get all the 1000 coins and invitee gets nothing, in a equal reward group both the inviter and invitee get 500 coins each, and an inviter in the generous reward group gets nothing but the invitee gets all the 1000 coins. Here, 1000 virtual coins are equivalent to $1 in worth[13], which compares well with the average price of such online apps. It bears mention that we do not consider the case where both inviter and invitee 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.

[13] The reward cannot be redeemed as cash but can be used for various in-app purchases.

As mentioned earlier, the mobile application also gave reminder notifications[14] 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. 3a shows the 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 inviters and invitees also received messages informing them about the rewards they received. These sample messages are shown in Fig. 3b. It is worth noting here that for the selfish reward group the app only informs the inviter about the reward and does not reveal to the invitee that the inviter 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.

Figure 3a: Sample reminder notifications received by inviters of different treatment groups

[14] 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 treatment groups. The difference in results we observe across the treatment groups is therefore driven by the incentive schemes.

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 3b: Sample messages received by inviters and invitees of different treatment groups upon successful referrals

5. Analyses and Results

5.1 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 experiment, there were 2130 players in total who adopted the app, out of which about 1702 were organic adopters (non-invited users who discovered the app on their own).

Group	Referral Reward mechanism	Inviter Incentive (%)	Invitee Incentive (%)	Organic Users
Control Group	No rewards, no reminders	0	0	185
Treatment Group (T0) – No reward, reminders	No rewards, reminder notifications	0	0	377
Treatment Group (T1) – Selfish reward	Inviter gets 1000 virtual coins	100	0	363
Treatment Group (T2) – Equal reward	Inviter and Invitee both get 500 virtual coins each	50	50	384
Treatment Group (T3) – Generous reward	Invitee gets 1000 virtual coins	0	100	393

Table 3: Summary of experiment groups and incentive schemes

For each user, we 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). We 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 experiment phase of the trial (April 21) and the day when the user actually joined the experiment by updating (for existing users) or downloading their app (for new users).

In addition, we collect all log-in and gaming activity for the users in our sample for the pre-treatment and experiment 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, we 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).

5.2 Pre-treatment Balance

We 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 from the pre-treatment phase for the control group (labeled as C) and the four experimental groups pooled together (labeled T) is shown in Table 4. As demonstrated in Table 4, 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 2015).

Group	Variable	Est.	SE	t-value	p-value
C	login_days	2.4706	0.7332	0.93	0.3525
T	login_days	2.0132	0.1431		
C	login_hours	3.4118	1.2219	0.45	0.6519
T	login_hours	3.0132	0.2629		
C	game_count	0.5882	0.3436	-0.75	0.4523
T	game_count	1.2914	0.3100		
C	game_total_player	2.6471	1.4974	-0.60	0.5521
T	game_total_player	4.5166	1.0370		
C	game_ave_player	4.7000	0.7000	1.72	0.0947
T	game_ave_player	3.6809	0.1726		
C	game_total_time	281.3	154.3	-0.56	0.5777
T	game_total_time	444.8	96.5952		
C	game_ave_time	528.9	101.6	0.93	0.3608
T	game_ave_time	411.4	38.0306		
C	location_count	1.2941	0.2539	0.15	0.8832
T	location_count	1.2583	0.0766		
C	invite_count	0.1176	0.1176	-0.13	0.8944

T	invite_count	0.1391	0.0524		
C	app_update_date	10.9412	2.4933	-0.05	0.9566
T	app_update_date	11.1126	1.0166		

Table 4: Summary statistics of the pre-treatment behavior across treatment and control for existing (pre-trial) users

5.3 Effects of Incentive Structure on the Number of Invitations

In the analysis, we focus our study on the behavior of the 1702 organic adopters (i.e., those who discovered the mobile game application from the app store) 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 inviters[15].

We begin our analysis by exploring changes in number of invites that were induced by our treatment over the incentivized period. Given that our dependent variable *invite_count* is a count variable, we run a Poisson regression using treatment as an independent variable uncorrelated with the residual. As demonstrated in Table 5, only the average effect of generous treatment on new invites is significant. This result is even more evident in Table 6 and Figure 4, which show the % change in the number of new invitees by players in generous group relative to the players in the control group. These results show that most of the gains come from an increase in invitation by the generous group players, who have fewer zero invites and more 1, 2, or 3 new invitees compared to the players in the control groups.

[15] 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.

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	-3.8341	0.5000	-4.8140	-2.8541	58.80	<.0001
Treatment 0: No reward, reminders	0.0987	0.1443	-0.1842	0.3816	0.47	0.4942
Treatment 1: Selfish reward	0.5815	0.5669	-0.5297	1.6927	1.05	0.3051
Treatment 2: Equal reward	0.4422	0.2739	-0.0946	0.9789	2.61	0.1064
Treatment 3: Generous reward	0.3745	0.1790	0.0236	0.7254	4.38	0.0365

Table 5: The result of Poisson model

Number of new users	Control	Generous	Control%	Generous%	%Change
0	182	375	98.38%	95.91%	-1.96%
1	2	9	1.08%	2.30%	112.92%
2	1	4	0.54%	1.02%	89.25%
3	0	3	0.000%	0.77%	300.00%
Total	185	391			

Table 6: % change in the number of new invitees between control and generous groups

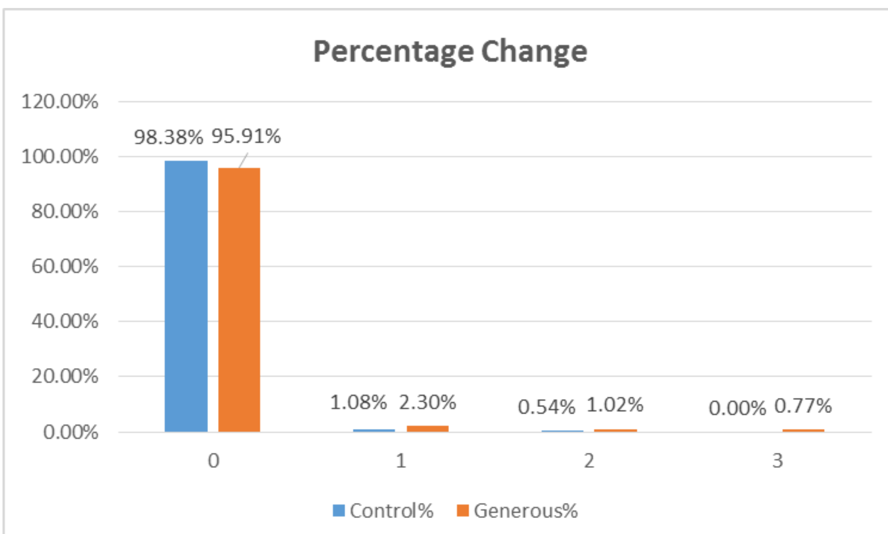

Figure 4: Comparison of the number of new invites between generous and control group

These results indicate that the test groups with no reward but only notification, the selfish referral reward (i.e., inviter 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 1, 2, and 3 adoptions than the players in the control group. This suggests that some pro-social or altruistic motivations tend to dominate the egocentricity in the referral process.

While prior literature has limited its attention on the number of referrals at the aggregate level, our micro-level data allows us to dig deeper. In particular, analysis at an aggregate (say monthly) level may not reveal the temporal and other patterns hidden in the data, in particular regarding differences in the referral behavior between new and existing users. To gain a more granular understanding of how referral reward scheme increases the number of referrals, we use richer panel data that allows variation across units as well as time. The result of the analysis is reported in the following sections.

5.4 Effects of Incentive Schemes on number of Invitations using Panel Data

Our panel data is based on the information recorded about the organic users of the mobile game app in the various treatment groups (as reported earlier in Table 3). On every day *t*, we collected the following data (Table 7), for each user:

Notations	Variable Descriptions
$\boldsymbol{InviteCount_{i,t}}$	Number of invites by user *i* at time *t*
$\boldsymbol{Treatment\_N_{i,t}}$	Whether the user *i* in treatment group *N* is in the incentivized period (1 = incentivized period, 0 = others)
$\boldsymbol{GameCount_{i,t-1}}$	Number of games a user *i* played at time *t-1, i.e.*, the previous day

Table 7: Notations and Variable Description

The variables $InviteCount_{i,t}$ is our DV and $Treatment\_N_{i,t}$ is the indicator for treatment in a specific incentive group. The lagged variable $GameCount_{i,t-1}$, which captures whether the user has been engaged with the app in the recent past is a control for individual users. In this real-world field trial, as mobile gamers are loathe to provide personal data, we do not have any demographic data (*e.g.,* age, gender) about users. As some of these omitted variables can be correlated with the predictor or independent variables included in the model, we performed the Hausman test (Greene 2008), which rejected the random effects model[16]. Therefore, we use a two-way fixed effect model with individual & time dummies[17].

$$\begin{aligned} InviteCount_{i,t} \; &= \alpha_0 + \alpha_1 Control_{i,t} + \alpha_2 Treatment\_0_{i,t} + \alpha_3 Treatment\_1_{i,t} \\ &\quad + \alpha_4 Treatment\_2_{i,t} + \alpha_5 Treatment\_3_{i,t} + \alpha_6 GameCount_{i,t-1} \\ &\quad + \delta_t + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

We present the results on the coefficients of our 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, only equal split reward and generous rewards are both positive and significant. The estimates show that the equal split reward scheme and the generous reward scheme generates 1.8 and 3.8 times more successful invites (adoption), respectively, than the control group. A robustness check without the $GameCount_{i,t-1}$ variable, which shows similar qualitative results, is provided in Appendix Table A1.

In comparison to the previous results of the simple Poisson regression on the aggregate data, this analysis with the panel data allows us to see that both the equal split reward and generous reward schemes are significant in increasing the number of invited adoptions. This is likely because the panel data analysis not only picks up the causal relation between the incentive schemes and the net count of invited adoptions, but also the

[16] The Hausman test for random versus one-way (individual) fixed effect has a t-value = 674.29, p <0.0001, hence random effects estimator is rejected.

[17] Wald test for the joint significance of time-dummies marginally rejects the null hypothesis (Chi2(42) = 55.88, p = 0.074) that they are not significantly different from 0, and hence, a two-way (individual and time) FE model is preferred.

temporal information of which types of users (*i.e.,* new versus existing) respond more to which type of incentive schemes.

Effect	Estimate	SE	t Value	Pr > |t|
Intercept	-0.00338	0.0145	-0.23	0.8154
GameCount_(t-1)	-0.01622	0.00145	-11.21	<.0001
Control	0.002054	0.00241	0.85	0.3939
Treatment_no reward, reminders	0.001549	0.00184	0.84	0.3996
Treatment_selfish reward	0.001262	0.00183	0.69	0.4902
Treatment_equal reward	0.00371**	0.00181	2.05	0.0408
Treatment_generous reward	0.00791***	0.00178	4.45	<.0001

Table 8: Effect of difference incentive schemes on number of invites for organic users (Two-way fixed effects, DV: Invite count)

5.5. Heterogeneity Effects

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), we therefore expect that the effect of incentive scheme on inviter's behavior would also change over time. If so, understanding the factors that influence the inviter's behavior over time an important component of the design of successful referral programs. Therefore, we conduct a secondary analysis to understand the underlying mechanisms of the observed effects. Specifically, we examined heterogeneity in the treatment effect around the time the user joined the site. Table 9 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 experiment) and new users (users who joined the site during the experiment).

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		
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	invite_count	0.0385	0.00705	-2.90	0.0038
1	invite_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 9: Summary statistics of the behavior across existing and new user

As is evident from Table 9, existing users are statistically different from new users in the game-related attributes. Therefore we report the subsequent statistics and results separately for the existing users and new users. As demonstrated in Table 10, results from this analysis show that there are heterogeneous effects of incentive schemes on referrals with respect to the type of the user[18]. Results of the two-way fixed effects model show that the equal split reward increases the number of invited adoptions for both new and existing users. However, only new users respond to the split reward scheme to positively increase the number of invited adoptions. In contrast, existing users respond to the generous reward scheme to positively promote invited adoptions. In Table A3 of the Appendix, we

[18] A robustness check for the effect of incentive schemes on number of invites for existing and new users when the lagged game count is not included yields similar results and is provided in Table A2 of the Appendix.

show the robustness of these findings by excluding 5% of both existing and new users who joined just before or after the treatment started.

User type	New users				Existing users			
Effect	**Estimate**	**SE**	**t Value**	**Pr > |t|**	**Estimate**	**SE**	**t Value**	**Pr > |t|**
Intercept	-0.00315	0.0140	-0.23	0.8213	-0.00419	0.0136	-0.31	0.7573
Game_Count_(t-1)	-0.01845	0.00158	-11.71	<.0001	-0.00839	0.00371	-2.26	0.0238
Control	0.000827	0.00250	0.33	0.7405	0.01296	0.00807	1.61	0.1082
Treatment_ no reward, reminders	0.001829	0.00193	0.95	0.3438	0.001477	0.00591	0.25	0.8028
Treatment_ selfish reward	0.001116	0.00190	0.59	0.5567	0.005687	0.00637	0.89	0.3719
Treatment_ equal reward	0.00395**	0.00188	2.10	0.0354	0.004778	0.00631	0.76	0.4491
Treatment_ generous reward	0.007236***	0.00185	3.91	<.0001	0.014436**	0.00606	2.38	0.0173

Table 10: Effect of incentive schemes on number of invites for new and existing users (Two-way fixed effects, DV: Invite count)

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. Specifically, the results demonstrate the existence of generous or altruistic behavior among a wide user base. Tapping into this latent happiness experienced by users from pro-social spending (Dunn 2013) can be useful in developing successful peer referral reward strategies for viral adoption of social games, and more broadly for communal digital goods.

Additionally, we found that equal split and generous reward schemes can dominate selfish referral schemes in increasing number of referrals. This is surprising based on the fact that selfish scheme is the most commonly used incentive scheme in referral reward programs. We suggest that peer perception may play an important role in the referral process. According to metaperception theory, when a referral is rewarded only to the inviter, an inviter might think that the invitee may perceive the referral as being driven by desire for reward rather than intrinsic motivation (Wirtz et al. 2012). Thus, while an incentive increases the likelihood of WOM, metaperception process can prevent referrals when the incentive for referral is rewarded only to the inviter.

Our secondary analyses also demonstrate that the inviters react to different incentive schemes depending on how long they have been playing the game. While equal generous reward increase the number of invites for both new and existing users, only the new users respond to the equal split scheme as well. This difference may be caused by guilt accumulation among users over time, which makes existing users behave generously, whereas relatively new users are not averse to keeping a portion of the reward for themselves. Another possibility may be that new users initially invite close family and friends who are easy to recruit, whereas over time it becomes harder to get new people to play the game with, unless the inviter is offering a generous reward to the invitee. And hence, existing users in only the generous group were being able to invite more new players than other treatment groups.

6. Conclusions & Future Directions

Understanding how incentive structure causally impacts the offline diffusion of products through WOM is a crucial step in developing referral reward strategies for viral adoption of digital goods. We explored this issue by designing a randomized field trial in which we tested the effectiveness of selfish, equal, and generous referral rewarding schemes. The context of our experiment was a mobile social game application with no prior brand history and other priming effects, which allowed us to design a clean study on the effect of *online referral reward structure* on the *offline diffusion* of the product.

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 inviters' behavior and rarely considered incentive sharing schemes in which both parties may receive rewards. We contribute to the literature by studying how one important mechanism of social contagion, offline word of mouth, is causally influenced by the design of the referral incentive scheme, namely, selfish reward, equal split reward, and generous reward schemes. The findings of our study are thus relevant to creating referral programs to promote WOM based adoption of digital goods.

The study also provides several opportunities for further research. One aspect that this trial was not meant to uncover the exact psychological reasons behind the user's referral behavior, but to study which of the referral incentive scheme works best for maximizing offline word-of-mouth based adoption. However, results showing the efficacy of the generous scheme among the entire user base demonstrate the strong role of happiness from pro-social behavior in creating diffusion in social networks. Similarly, the failure of the selfish reward scheme hint towards the potential role of guilt felt by users in benefitting from invitations to 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 influence one possible motivation at a time while controlling for all the others.

Lastly, our results show that there is a heterogeneity effect 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. This was observed in the reported differences between the referral behavior of the existing and the new users in our trial. This suggests that for maximizing adoption, 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 generous to selfish reward based on how long a user has been playing the game)? (ii) Does this behavior hold more generally for apps that do not have a social setting? We intend to address these questions by designing a new set of randomized field experiments that assigns users to test groups which differ in the duration of consecutive generous and split incentive periods.

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Appendix

Table A1: Effect of incentive schemes on number of invites for organic users (Two-way fixed effects, DV: Invite count)

Effect	Estimate	SE	t Value	Pr > |t|
Intercept	-0.00335	0.0145	-0.23	0.8173
Control	0.00191	0.00241	0.79	0.4286
Treatment_no reward, reminders	0.001479	0.00184	0.80	0.4220
Treatment_selfish reward	0.001155	0.00183	0.63	0.5285
Treatment_equal reward	0.003529*	0.00182	1.94	0.0520
Treatment_generous reward	0.007377***	0.00178	4.14	<.0001

The Hausman test rejects the random effects model (t-value =14.27, p = 0.0268), and so a FE model is used.

Table A2: Heterogeneity Analysis for Organic users of Table A1. Effect of incentive schemes on number of invites for new and existing users (Two-way fixed effects, DV: Invite count)

User type	New users				Existing users			
Effect	Estimate	SE	t Value	Pr > |t|	Estimate	SE	t Value	Pr > |t|
Intercept	-0.00312	0.0140	-0.22	0.8235	-0.00404	0.0136	-0.30	0.7662
Control	0.000666	0.00250	0.27	0.7902	0.012815	0.00807	1.59	0.1123
Treatment_ no reward, reminders	0.001758	0.00194	0.91	0.3637	0.00147	0.00592	0.25	0.8037
Treatment_ selfish reward	0.000931	0.00190	0.49	0.6248	0.005823	0.00637	0.91	0.3608
Treatment_ equal reward	0.003681*	0.00188	1.96	0.0504	0.004896	0.00631	0.78	0.4381
Treatment_ generous reward	0.006674***	0.00185	3.60	0.0003	0.014063**	0.00606	2.32	0.0204

Table A3: Effect of incentive schemes on number of invites for organic users excluding 5% of existing/new users who joined the site right before and after 4/21 (Two-way fixed effects, DV: Invite count)

User type	New users				Existing users			
Effect	Estimate	SE	t Value	Pr > |t|	Estimate	SE	t Value	Pr > |t|
Intercept	-0.00342	0.0143	-0.24	0.8106	-0.00431	0.0142	-0.30	0.7611
Game_Count_(t-1)	-0.01846	0.00161	-11.44	<.0001	-0.00855	0.00385	-2.22	0.0265
Control	0.001194	0.00266	0.45	0.6533	0.015467	0.00884	1.75	0.0803
Treatment_ no reward, reminders	0.000895	0.00206	0.43	0.6643	0.000683	0.00625	0.11	0.9129
Treatment_ selfish reward	0.001419	0.00204	0.70	0.4858	0.005641	0.00679	0.83	0.4062
Treatment_ equal reward	0.004247**	0.00199	2.13	0.0330	0.005482	0.00680	0.81	0.4200
Treatment_ generous reward	0.007789***	0.00199	3.91	<.0001	0.013963**	0.00642	2.17	0.0298

Table A4: Pairwise comparisons of the pre-treatment behavior across control and treatment for existing users

Variable	Group	Est.	SE	t-value	p-value
login_days	C	2.4706	0.7332		
	T0	1.9286	0.2490	0.89	0.3746
	T1	1.6571	0.1687	1.45	0.1534
	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		
	T0	2.6667	0.4279	0.73	0.4692
	T1	2.2571	0.3389	1.19	0.2415
	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		
	T0	1.4048	0.6791	-0.75	0.4587
	T1	0.9429	0.5053	-0.46	0.6456
	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		
	T0	4.9286	2.3940	-0.59	0.5606
	T1	3.2286	1.6073	-0.23	0.8197
	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		
	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		
	T0	502.7	245.5	-0.55	0.5819
	T1	352.3	160.5	-0.28	0.7817
	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		
	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		
	T0	1.1905	0.1240	0.41	0.6831
	T1	1.0286	0.1328	1.02	0.3109
	T2	1.2222	0.1443	0.26	0.7930

	T3	1.5789	0.1946	-0.84	0.4021
invite_count	C	0.1176	0.1176		
	T0	0.1429	0.0874	-0.16	0.8726
	T1	0.1714	0.1263	-0.27	0.7884
	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		
	T0	12.0238	1.9250	-0.32	0.7528
	T1	11.4000	2.2395	-0.13	0.9007
	T2	14.3611	2.3167	-0.90	0.3709
	T3	6.7632	1.4994	1.50	0.1404