ABSTRACT

Title of Document: **ENGINEERING DIGITAL SHARING PLATFORM TO CREATE SOCIAL CONTAGION: EVIDENCE FROM LARGE SCALE RANDOMIZED FIELD EXPERIMENTS.**

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Peer-to-peer information sharing has fundamentally changed customer decision-making process. Recent developments in information technologies have enabled digital sharing platforms to influence various granular aspects of the information sharing process. Despite the growing importance of digital information sharing, little research has examined the optimal design choices for a platform seeking to maximize returns from information sharing. My dissertation seeks to fill this gap. Specifically, I study novel interventions that can be implemented by the platform at different stages of the information sharing. In collaboration with a leading for-profit platform and a non-profit platform, I conduct three large-scale field experiments to causally identify the impact of these interventions on customers' sharing behaviors as well as the sharing outcomes.

The first essay examines whether and how a firm can enhance social contagion by simply varying the message shared by customers with their friends. Using a large

randomized field experiment, I find that i) adding only information about the sender's purchase status increases the likelihood of recipients' purchase; ii) adding only information about referral reward increases recipients' follow-up referrals; and iii) adding information about both the sender's purchase as well as the referral rewards increases neither the likelihood of purchase nor follow-up referrals. I then discuss the underlying mechanisms.

The second essay studies whether and how a firm can design unconditional incentive to engage customers who already reveal willingness to share. I conduct a field experiment to examine the impact of incentive design on sender's purchase as well as further referral behavior. I find evidence that incentive structure has a significant, but interestingly opposing, impact on both outcomes. The results also provide insights about senders' motives in sharing.

The third essay examines whether and how a non-profit platform can use mobile messaging to leverage recipients' social ties to encourage blood donation. I design a large field experiment to causally identify the impact of different types of information and incentives on donor's self-donation and group donation behavior. My results show that non-profits can stimulate group effect and increase blood donation, but only with group reward. Such group reward works by motivating a different donor population.

ENGINEERING DIGITAL SHARING PLATFORM TO CREATE SOCIAL CONTAGION:
EVIDENCE FROM LARGE SCALE RANDOMIZED FIELD EXPERIMENTS

By

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Chapter 1: Overview

Recent advances in digital technologies have provided firms unprecedented ability to monitor consumer behavior and provide information across all stages of marketing funnel. With the availability of rich data, strong processing power and new intervention channels, centralized information provision approaches -- such as search advertising, context-based display ads, personalized email, tailored messaging, hyper-localized mobile targeting -- have improved dramatically. In the era of 'Big Data', firms can increasingly deliver 'the right information to the right person at the right time' in a directed and controlled fashion.

Despite these improvements, an alternative paradigm of information provision – peer-to-peer information sharing -- remains of central importance in customer decision-making process. Rather than from a centralized and controlled source, information in peer-to-peer sharing is served by friends and peers of the customers that are dispersed in the crowd. Such a decentralized information provision approach may outperform or complement direct information provision in at least three ways: 1) (knowledge advantage) due to disperse nature of knowledge (Hayek 1945), peers of the customer often have *more and different* information about the the preferences of their social connections than the firm; hence the information they provide is often more relevant to the customer; 2) (persuasion advantage) the information from peers is usually more credible and persuasive; 3) (social advantage) in the case of consuming products with network externality, information sharing among peers essentially serves as a way for group coordination and could lead to collective consumption with higher surplus. Though peer to peer information sharing offers various desirable properties, firms have had little control over this process in traditional settings.

With the wide spread growth of digital technologies, a large volume and variety of information is now shared through digital sharing platforms in the form of website-mediated emails, social media posts, and mobile messages. An interesting aspect of the digital information sharing is that while consumers are able to quickly disseminate online word of mouth about firms and products, firms are also increasingly able to mediate these interactions among customers. Firms have transitioned from being passive observers of information sharing to becoming more active mediators and moderators (Godes et al 2005). Today's technologies provide firms unprecedented capacity to mediate and control various granular aspects of the information sharing process including - the motivations of the referrers, the choice and recipients, and the message, among others. Firms now could engineer digital sharing platforms to amplify the advantages of information sharing and create social contagion. For the first time, firms can apply centralized interventions on decentralized sharing process thus enjoy the benefits of the both information provision paradigm.

Despite the importance of information sharing and newly available interventions, little research has been done on how firms can strategically use and impact them. This represents an exciting research opportunity (Godes et.al. 2005). In particular, there are very few studies that have examined the optimal design choices for a firm seeking to maximize returns from information sharing. My dissertation seeks to fill this gap.

Specifically, my dissertation studies novel interventions that can be implemented by firms on digital sharing platform (for example, interventions in the form of message design, incentive design, and group rewards) at different stages of the information sharing process. In collaboration with a leading for-profit platform and a non-profit platform, I combine large-scale field experiments with big data to causally identify the impact of these interventions on customers' sharing behaviors as well as the sharing outcomes. In addition to identification of main effect, the exogenous variation from experiment and the rich heterogeneity in big data allows me to infer and test underlying mechanism at work. In this way, my dissertation will also help build a better understanding on the antecedents and consequence of information sharing

The three essays are summarized as following: the first essay examines whether and how a firm can enhance social contagion by simply varying the message shared by customers with their friends. I focus on two key components of information contained in the messages – information about the sender's purchase status prior to referral, and information about the existence of referral rewards – and their impacts on the recipient's purchase decision and further referral behavior. In collaboration with an online daily deal platform I design and conduct a large scale randomized field experiment to identify the effect of each message component, as well as the interaction effects between them, in creating social contagion. I find that small variations in message content can have a significant impact on both recipient's purchase and referral behaviors. Specifically, I find that i) adding only information about the sender's purchase status increases the likelihood of recipients' purchase, but has no impact on follow-up referrals; ii) adding only information about referral reward increases recipients' follow-up referrals, but has no impact on purchase likelihood; and iii) adding information about both the sender's purchase as well as information about the referral rewards increases neither the likelihood of purchase or follow-up referrals. The study also examines the underlying mechanisms (i.e. social learning and social utility) that drive social contagion by exploiting the rich heterogeneity in product, recipient, sender and social tie characteristics.

The message design intervention is implemented to influence recipients' behavior only *after* the sender has organically initiated the shares. The firm could also take a more active role and engage senders when they reveal willingness to share. The second essay studies whether and how a firm can uncover the (self-, other-, or group-regarding) motive underlying an individual's share, and design novel incentives (e.g. shareable promo code) to influence the individual's purchase and further sharing decision. Specifically, a large number of customers share product information with each other everyday. While such sharing indicates the purchase intent of either sender or recipient (or both), most of these 'shares' do not lead to successful conversions. With increasing availability of data on sharing traffic, as well as the ability to process such data in real time, firms can now monetize the sharing traffic by targeting customers in the share. In collaboration with an online daily deal platform, I design and conduct a large scale field experiment to examine the impact of incentive design on sender's purchase as well as further referral behaviors by randomly assigning more than 20,000 promotional emails to senders who shared but did not purchase. I find evidence that incentive structure has a significant, but interestingly opposing, impact on both outcomes; ii) the firm can customize incentives based on senders' sharing motives predicted from their behavioral traits.

While the first two studies focus on intervention on individuals who have already expressed willingness to share, it is also equally interesting to learn how firms could motivate individual to share information at the first place. Specifically, my third essay examines how non-profits can leverage mobile messaging and design novel incentives to motivate donors to coordinate amongst themselves offline and donate in a group. I design a large field experiment to causally identify the impact of different types of information and incentives on donor's self-donation and group donation behavior. The results show that 1) both individual reward and group reward have an positive effect on blood donation, but only group reward increase group donation significantly; 2) donors who donate in a group donate significantly more blood; 3) group reward is working through a novel mechanisms and motivating a different donor population from that of individual reward. In summary, the results suggest that non-profits can stimulate group effect and increase blood donation, but only with appropriate economic incentives.

Overall, the findings from the three studies will provide valuable insights for platforms and social enterprises on how to engineer digital platforms to create social contagion. The rich data from randomized experiments and complementary sources (archive and survey) also allows me to test the underlying mechanism at work. In this way, my dissertation provides both managerial implication and theoretical contribution to the phenomenon of peer-to-peer information sharing.

Chapter 2:
Essay 1 -- Creating Social Contagion through Firm-Mediated Message Design: Evidence from a Randomized Field Experiment

2.1. Introduction

Online social interactions in the form of website-mediated emails, social media posts, and mobile messages, are becoming increasingly important and have been studied extensively (Godes et al. 2005, Trusov et al. 2009, Schmitt et al. 2011, Skiera et al. 2014, Berger 2014, Aral and Walker. 2011a, 2012, Bapna and Umyarov 2014). An interesting aspect of the online setting is that while consumers are able to quickly disseminate online word of mouth about firms and products, firms are also increasingly able to mediate these interactions among customers. Firms have transitioned from being passive observers and moderators to becoming more active mediators (Godes et al. 2005) of online social interactions and referrals.

An important element of online social interactions and the primary medium by which social influence is transmitted is the message that is shared between senders and recipients. In the case of "firm-mediated messaging" among users, while the sender can choose the recipients with whom she shares the message, the firm nevertheless, has the ability to control several aspects of the message. Such firm-mediated messaging is increasingly the norm in a large number of online websites, retailers, and social platforms. Despite the increasing use of such mechanisms by firms online, there is very little understanding of how different messages impact social contagion. Given the ability of the firm to partially control the content of the message that is shared between the sender and the recipient, my study seeks to examine *whether* and *how* a firm can enhance social contagion, by simply varying the message shared by customers with their social connections.

Identifying the effect of message content on social contagion (recipient's purchase and further referrals) has been traditionally difficult for two reasons: first, the content of the message in interpersonal communications is usually unobservable to researchers (Godes et al. 2005); second, and probably more fundamental, is the issue of endogeneity (Hartmann et al. 2008), i.e. content of the message may be correlated with the tie strength, the characteristics of the recommended product as well as external incentives, as interpersonal communications are often strategic (Crawford & Sobel 1982). Several approaches for identifying peer effects have been proposed, including dynamic matched sampling (Aral.et.al. 2009), structural models (Ghose and Han 2010) and instrumental variables (Tucker 2008). However, most of above methods are not appropriate to study the causal impact of message design on referral outcomes because of unobserved data and potential endogeneity. I therefore design and conduct a large-scale randomized field experiment to test the causal impact of message design on social contagion.

I focus on two key components of information contained in the message – information about the sender's purchase of the product prior to referral, and information about the existence of monetary reward for referrals – and their impacts on two key outcomes – the recipient's purchase decision, and the recipient's further referrals (see Figure 1). In collaboration with a leading daily deal platform in the US, I design a randomized field experiment to study the causal impact of each message component, as well as their interaction effects, in creating social contagion. I create four versions of the message by including or excluding each message component, and randomly assign the shared messages into one of these four variants (see Figure 2). I find that small variations in the message content can have large impacts on both recipient's purchases and referral behaviors. The results are both statistically and economically significant, suggesting that a minor change in message design at zero cost can potentially have a substantial impact on customer behaviors and firm's profits. Specifically, I find that i) adding information about the sender's purchase status increases the likelihood of recipients' purchases by more than 15%, but has no impact on follow-up referrals; and ii) adding information about the referral reward increases recipients' follow-up referrals by more than 60%, but has no impact on purchase likelihood; iii) when the two components of information are made available, surprisingly, neither purchase likelihood nor follow-up referrals increase. The negative interaction effect between the two components highlights a potential tradeoff faced by the firm in designing the message: should the firm increase adoption or enhance diffusion? Detailed analysis reveals that firms should design messages that can increase adoption when baseline adoption rate is relatively low (as in my case), but may choose message that encourages diffusion when baseline adoption rate is relatively high (e.g. free products, content and services). My findings also indicate that implementation of the optimal message design (with sender's purchase status) can lead to a significant increase in net profits, even after accounting for the cost of referral rewards.

I then unpack the black box to investigate the underlying mechanisms at work. Prior literature (Zhang 2010, Aral et al. 2011) suggests two primary mechanisms – social learning, and social utility (or local network effects) -- may be at work. I am able to distinguish between these two underlying mechanisms by exploiting the rich heterogeneity in product, sender, recipient, and social tie characteristics. In the process, my study not only contributes to examining whether message design can enhance social contagion, but also sheds light on the underlying mechanisms at work, in line with the recent call by researchers (Iyengar et al. 2011b, Godes 2011, Aral 2011) who highlight the need to move from understanding “whether” to “why” in social contagion research.

Information about the sender’s purchase of the deal serves as a social learning cue and such information could positively influence the recipient’s belief about the quality of the product or service, and consequently increase her likelihood of purchase. I find that this is indeed the case for recipients with less experience as compared to those with greater experience, for less popular deals as compared to more popular ones, and for purchases at early stage of product sales cycle as compared to those in later stages – instances where information gleaned from the sender’s purchase status is more valuable. I also find that, it is under these same conditions characterized by higher uncertainty, adding information about the presence of sharing rewards attenuates the positive effects of sender’s purchase information.

Information about the sender’s purchase status could also serve another important purpose: for social products that are characterized by positive local network effects (e.g. social events), knowledge about a friend’s purchase of a product/service could provide additional utility to the recipient and increase her likelihood of purchase. I find this is indeed the case for social products as compared to stand-alone products, indicating the role of social utility in driving conversion.

My empirical findings suggest that both mechanisms are at play, social utility, in the case of social products/services, and social learning in instances of higher uncertainty. Identifying these different underlying mechanisms is not only of theoretical importance but also of practical value as firms can adopt alternative mechanisms to drive conversions depending on whether social learning or social utility is at work.

Identifying optimal design of firm-mediated message at an aggregate level is a valuable endeavor, but not the end in itself. With the availability of large amount of data on the behaviors of senders and recipients and their historical interactions, as well as the ability to process requests in real time, firms can actually personalize firm-mediated messages at the product level or even at an individual level. Thus, it is crucial to identify potential moderators at various levels. While personalization is a common practice in the context of firm-customer interactions, personalization of firm-mediated customer-customer social interaction is still in its infancy. To investigate its potential, I further explore the heterogeneity in sender characteristics as well as social tie characteristics, in additional to the product and recipient characteristics discussed above. I find that both sender characteristics (for instance, the target-iveness of the share) and social tie characteristics (for instance, the reciprocity of historical sharing) strongly moderate the effect of message design on social contagion.

Finally, I examine the welfare implications of message design. While social learning may lead to more purchases and benefit the seller, it may nevertheless, lead to irrational herding and harm customers. On the other hand, social utility is always welfare enhancing. Using customer feedback data from email surveys, I find evidence that message design enhances customer experience in general, and especially so for social products.

My study is among the first to analyze the potential of firm-mediated messaging and the findings of the study not only add to our understanding of the role of different messages on referral outcomes, but also provides valuable guidelines for optimal design of such information sharing mechanisms at an aggregate level as well as a more granular level.

2.2. Related Research

There is a growing literature on social interactions (see Godes et al 2005, Berger 2014, Libai et al. 2011 and Hartmann et al. 2008 for excellent reviews) and my study is closely related to three streams of research that spans marketing, information systems and economics, among others.

The first stream of research examines the causal effect of peer influence. Researchers have used secondary data (Aral et al. 2009), lab experiments (Asch 1951), simulations (Goldenberg et al. 2001), and field experiments (Cai 2014, Miller and Mobarak 2014) to study the effects of peer influence across a wide variety of settings. Observational studies (e.g. using propensity score matching or instrumental variables) need to separate peer influence from homophily (Ma et al. 2014), marketing efforts (Van Den Bulte and Lilien 2001), simultaneity (Hartmann et.al. 2008), and often have difficulty in cleanly identifying influence as well as underlying mechanisms (Manski 1993). Such problems are even more acute for my focal research questions, as researchers usually cannot observe the message content in interpersonal communications. More importantly, the choice of message content is fundamentally endogenous (as it can be correlated with social-tie characteristics, sender characteristics, and product characteristics, among others). An emerging stream of research has used field experiments to separate social influence from homophily (Aral and Walker 2011a, Bapna and Umyarov 2014), and to identify the impact of specific drivers of social influence (Aral and Walker 2012, 2014). I complement this literature and leverage a large-scale randomized field experiment to identify the effect of message design on social contagion. While previous experiment has focused on creating exogenous variation on sender's behavior such as adoption (Bapna and Umyarov 2014) and sharing (Aral and Walker 2011), I devise a novel randomization approach and create exogenous variation at more granular level (i.e. message content), conditional on sender's organic adoption and sharing decision. I also demonstrate how firms (such as the daily deal platform) can utilize such field experiments to identify optimal message design.

Previous studies on peer influence (Aral et al. 2012, 2014, Iyengar et al. 2011a, Bapna and Umyarov 2014) have mostly focused on the effect of other's adoption on one's own adoption decision. However, at a more granular level, such influence is mediated by messages (online or offline WOM, or observational learning). My study, with its primary focus on firm-mediated messaging, extends the literature on peer influence by identifying the incremental contribution of different "components" of a message on social contagion outcomes. By varying different features within a message, I am able to decompose social influence at the component level. In addition to the main effects, the wide range of product characteristics included in my study also enables me to differentiate between the two key mechanisms of social contagion: social learning (wherein the recipient infers the high quality of products from sender's purchase) and social utility or local network effects (wherein the recipient gets additional utility from sender's adoption of product, e.g. social events). Godes 2011 and Aral 2011 call for studies on the role of product characteristics in moderating social contagion. Taking advantage of the wide range of product included in my data, I am able to show that contagion effect becomes smaller for more popular products and for products in later stages in their lifecycle. I also identify additional moderators using sender's sharing pattern as well as historical social interactions and suggest optimal message design at granular level.

The second important stream of research relates to the study of online word of mouth. There is a growing body of work that examines the aggregate impacts of WOM on adoption and diffusion of products (Godes et al. 2004, 2009, Stephen and Galak 2012, Trusov et al. 2009). A more relevant stream of research is one that examines the underlying processes that drive consumer's WOM and their impacts. As noted by Berger (2014), prior work relating to online WOM has focused on the following key components - the sender, the recipient, the social tie characteristics, the channel, and the message. Prior research has examined the role of sender characteristics including the credibility and the motives of the source/sender (for instance, see (Tuk et al. 2009), transmitter activity (Stephen et.al. 2012), as well as the role of recipient's attitude towards a product (e.g. Stephen and Lehmann 2009), and how these impact the effectiveness of WOM. Katona et al. (2011), Golderberg et al. (2009), and Naylor et al (2011), among others have studied how the social ties between the sender and the recipients impact social contagion. As for the role of the channel, Berger and Iyengar (2013), have examined the implications of channel characteristics for the design of WOM campaigns. Of these key components of WOM, the message is widely considered as the most fundamental factor driving social influence (Berger 2014, Godes et al. 2005), and the role of the message on social contagion is perhaps the least understood. As far as the message in WOM is concerned, the focus has largely been on aggregate aspects of the message such as the valence of the message (whether it is positive or negative) and whether the message is emotional or factual (Berger and Milkman 2012). My study contributes to our growing understanding of the focal role of the WOM message on social contagion by examining how different components of the message can influence social contagion. More importantly, my study is among the first studies to examine the firm's role in the emerging phenomenon of firm-mediated WOM (Godes et al. 2005).

Another closely related stream of research is the role of observational learning in driving social contagion. Research in a number of disciplines (for instance, Banerjee 1992, Bikchandani, et al 1998, Chen et al 2011, Cai et al. 2007, Zhang 2010) has studied observational learning. Chen et al. (2011), for instance, compare the impacts of observation learning with online WOM and find that while negative WOM has a stronger impact than positive WOM, the opposite is true of observational learning. My study contributes to this stream of research by examining the impacts of observational learning in a context where observational learning is embedded within online WOM. My study focuses on the impacts of observability of two specific components of online WOM – the sender's purchase status and the referral rewards for the sender. As for sender's purchase status, previous studies (Tucker and Zhang 2011, Chen et al. 2011) have examined the effect of product popularity (others' purchases at aggregated level) on one's own purchase decision (learning from crowd). My study complements previous literature by using micro-level data to examine the effect of a friend's purchase information (transmitted by organic WOM) on one's own purchase decision (learning from friends). I also examine the underlying mechanisms of observational learning using rich heterogeneity in sender, recipient, product, and social-tie characteristics, and provide rich evidence that highlights observational learning at work. Finally, though separating saliency/attention from observational learning is notoriously difficulty (Cai et al. 2007), I am able to deactivate this channel with my experimental design (using same subject line in emails) and cleanly identify the effect of observational.

As for information about referral rewards in the message, there have been a number of analytical models examining the optimal design of referral rewards from firm's perspective (for instance see, Biyalogorsky et al 2001, Kornish and Li, 2010, Xiao et al 2011). A few experimental studies (Wirtz and Chew 2002; Ryu and Feick 2007) have examined the impact of referral rewards on the likelihood of referrals. A couple of studies (Tuk et al 2009; Verlegh et al 2013) that have focused on the role of rewarded referrals on recipient's purchase decision have been small scale lab experiments. Mine is the first large scale field experiment to examine the role of monetary rewards for the sender on both recipient's purchase and further referrals. By varying sender's purchase information in the message, my study also extends current work through analysis of the interaction effects between referral awards and recipient's perception of the sender. Finally, the rich heterogeneity in my data allows me to identify nuanced moderating effects (e.g. the role of moderating variables such as tie strength), and link them back to detailed mechanisms of social influence.

2.3. Research Context

In collaboration with a leading online daily-deal platform, I design a randomized field experiment to study the causal impact of firm-mediated message on recipient's behaviors. The platform offers a wide range of daily deals for local services and standard products at a high discount and has a large customer base. On each deal page on the firm's website, the platform provides channels through which customers (senders) can share these deals with their social connections. Customers (senders) can share deals with their friends both before and after purchase by clicking specific channel buttons which are prominently displayed. Specifically, senders who wish to share through email can add a recipient's email address in the pop-up window and click "send"[1]. For email referrals, the platform will then automatically deliver emails to each recipient's email address separately using a pre-defined message template[2]. The current experiment focuses on the post-purchase sharing through email. Every day, a large volume of shares is made by customers through the platform[3]. After purchasing the deal, the customer gets a voucher that she can use to redeem the specific service or product within a period of time (usually 6 months or more). The vast majority of senders have not actually consumed the service or product at the time of share.

The platform sometimes uses a referral program to encourage social interactions. To participate in this program, a user is first required to purchase a particular deal. Then, the user is given the option to share the deal with as many friends as desired. The user gets a referral reward when certain number of the recipients, as pre-determined by the platform, purchase the deal.

2.4. Experiment Design

While previous experiments on social influence (Aral and Walker 2011a, 2012, 2014, Bapna and Umyarov 2014, Miller and Mobarak 2014) have identified how users's adoption of a product/service influence others, the objective of this study is to identify the

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[1] The message that the recipients see does not appear in the window.

[2] Even though the sender may specify multiple recipients in a single 'send', each email is sent separately and hence, each recipient receives the email as a one-to-one personal share. Hence, I define each sender-recipient pair in a multi-recipient share as an "independent share".

[3] A fraction of the senders also share deals through their own channels (e.g. copy-paste the deal URL into their own social media or email account), leading to successful referrals. The firm has no control on the message content of such social interactions. My field experiment focuses only on senders using the firm's platform/website for sharing/referrals.

effect of message design, conditional on a user organically sharing the deal with her social connections. Specifically, my study seeks to understand the effect of two components of information in the message i) information about the sender's purchase status and ii) information about the referral reward program, on recipient's purchase and further referrals. I create four versions of message by varying the visibility of sender's purchase status and referral reward program, as illustrated in Figure 3. After the sender confirms her share by clicking the 'send' button, all of her messages are randomly assigned to one of the four test groups (Figure 4) (1 control (C), and 3 treatments (T1-T3)). The randomization happens after the sender's share and thus, the message content is completely orthogonal to the sender's sharing behavior. Any difference in the recipient's purchase and further referral behavior can therefore, be directly attributed to the difference in message design. Using the 2 x 2 design, I am able to identify the main effects as well as the interaction effects of both components in the message on the recipient's purchase and further referrals. Similar to Aral and Walker 2011, when analyzing effectiveness of sharing I focus on the initial senders, rather than recipients who share after they make a purchase from the initial sender's referral. I analyze effectiveness of recipient's sharing only to calculate the successful further referrals from her. In addition, when a recipient purchases the shared deal and initiates a new set of shares, she is randomly assigned to one of the four test groups. Thus, the difference in successful further referrals is mainly driven by difference in recipient's sharing behavior, rather than the message content (similar design choice is discussed Aral and Walker 2011a, 2011b).

Level of Randomization & Control of Contamination

My intervention (message design) by nature can happen at the level of each sender-recipient share. However, to prevent potential contamination, I design the randomization at the level of the sender, i.e., all recipients of a sender for a specific deal that is shared, receive the same message. Randomization at the level of the sender (rather than at the level of recipients) allows for better control of potential spillovers between control and treatment groups and helps ensure that the stable unit treatment value assumption (SUTVA) is not violated (Wooldridge 2012). Such spillovers are more likely to happen within the local network of a sender as compared to across senders' networks (Aral and Walker 2011a). For instance, two friends of sender S are much more likely to communicate about a specific deal (through sharing the deal or through other modes of communication) and influence each other's decision as compared to recipients of two different senders. (however this is still a possibility, and I later (see online Appendix 1) discuss approaches to mitigate this concern). My randomization design ('inside out') is similar to ones adopted in previous research (for instance see, Aral and Walker 2011b).

Ruling out attention/saliency as a Contagion Mechanism

In addition to identifying main effect of message design, I also carefully design my experiment to identify specific mechanisms underlying social contagion. As noted in previous literature (e.g. Godes 2011, Cai et al. 2007), contagion may be driven by several mechanisms including attention/saliency, social learning, local network effect, status competition, etc. In my context, the first three channels will be most prominent; Attention/saliency is expected to strongly influence contagion. For instance, the increased attention resulting from the awareness of a friend's purchase of an item could in itself lead to a higher likelihood of purchase. Since my focus is on the role of social learning and social utility, I utilize a two-stage structure to deactivate the role of *attention/saliency* in creating social contagion.

Specifically, I maintain the same subject line in the sharing email ("[Friend name] thinks you may like the product"). Thus, prior to opening the email, there should not be any difference in attention/awareness as the email and its subject line are exactly the same. Once the email is opened and read (indicating recipient is paying attention & interested in the content of the message), the contained information in the email is simple, clear, and concise and should not lead to any differences in product awareness or attention. Thus my design eliminates potential contamination that could arise from differences in awareness or attention and enables me to focus on the two mechanisms of interest. Moreover, since the sender's purchase status can attract increased attention from the recipient, I expect my current treatment effect to be stronger if such information is also incorporated into subject line of email. In future work, I plan to vary the subject line to further identify the role of saliency/attention in driving social contagion.

2.5. Data

The randomized field experiment lasted for a period of few weeks and resulted in a large and random sample comprising more than 20,000 unique senders (i.e. more than 5000 senders in each test group) sharing more than 5000 unique deals. The number of recipients who were exposed to the deals in my study period exceeds 50,000 (as a sender may share a deal with multiple recipients). The data for my study comes from customer-to-customer email shares/referrals through the platform. For every firm-mediated email share, I record the unique hashed identifier of the sender (customer ID), the recipient (hashed email address), the shared deal, as well as the assigned test group. I record the number of recipients the sender specifies in the batch of sent messages, the timestamp of share as well as purchase decisions of the recipient. I further augment the above main dataset with the historical data on sender and recipient's purchase history, the interactions between them as well as detailed characteristics of deals (price, category, subcategory, popularity, time stamp of every purchase of the deal, etc.). The resulting dataset enables me to analyze the impact of message design at a granular level (i.e. heterogeneous treatment effect, or moderating effect of sender, recipient, product and social tie characteristics). To control spillover, I follow the procedures as detailed in the online Appendix 1 and remove all the recipients who are exposed to more than one types of message during my experiment

2.6. Empirical Strategy

To identify the effect of each component of information on the recipient's likelihood of purchase and further referrals, I run the regressions (OLS, poisson, and negative binomial) of the following specification at the sender level without and with controls. A similar strategy is used in field experiment studies in economics and marketing, as illustrated in Duflo et al. (2008).

$$Y_j = \Sigma \beta_g * T_g + \text{error}_j$$

$$Y_j = \Sigma \beta_g * T_g + \textit{SenderChar}_j + \textit{ProductChar}_j + \text{error}_j$$

Y_j indicates the total number of referrals from sender j's share. Later I also use it to indicate alternative measures such as total net revenue brought by each sender's referral or total number of recipient's further referrals that originate from the sender. The dummy variable T_g indicates the test group that sender is assigned to. The omitted category is usually the baseline message in most of the cases but later, I use the message with only information on sender's purchase as the baseline to identify the attenuation effect. *SenderChar*$_j$ indicates sender level characteristics including the number of sender's past purchases and account length. $ProductChar_j$ indicates all product control variables including price of the deal, category of the deal and popularity of the deal. The error is clustered at deal level[4].

I also run additional models at the recipient level (OLS, probit and logit) using the following specification similar to Duflo et al. (2011).

$$Y_{ij} = \Sigma \beta_g * T_g + \text{error}_{ij}$$

$$Y_{ij} = \Sigma\beta_g*T_g + SenderChar_j + ProductChar_j + RecipientChar_i + SocialTieChar_{ij} + \text{error}_{ij}$$

Y_{ij} indicates individual i's purchase decision after receiving sender j's share. I also use it to indicate the recipient's further referrals as well as the recipient's feedback about the consumption experience. $RecipientChar_i$ indicates all recipient characteristics including number of past purchases and account length. $SocialTieChar_{ij}$ indicates the social-tie strength between the sender and the recipients based on sharing history. The error term is clustered at deal level. To further identify heterogeneous treatment effect of message design at both the sender and recipient level, I interact the moderating variables with the test group indicator and run the regression at recipient level using the following specification,

$$Y_{ij} = \Sigma \gamma_1 * T_g * \text{Indicator }(\text{ModeratingVar}_{ij} = 1) + \Sigma \gamma_0 * T_g * \text{Indicator }(\text{ModeratingVar}_{ij} = 0) + SenderChar_j + ProductChar_j + RecipientChar_i + SocialTieChar_{ij} + \text{error}_{ij}$$

where $\text{ModeratingVar}_{ij}$ can denote different moderating variables such as recipient's past purchase experience, tie strength, social-ness of the product and target-iveness of the share.

[4] For both sender level and recipient level analysis, I also run regression with errors clustered at sender-deal pair level, sender level or using a double cluster structure (Cameron et al. 2007). The standard deviations from all these choices are smaller than that in current model. My results are more significant under alternative clustering choices.

2.7. Empirical Findings

As a check of the randomization, I present in Table 1 the tests of equality of sender, recipient, product, and social tie covariates across the four test groups. The sample is well balanced across all the covariates, indicating that my randomization is at work.

2.7.1. Main Effect on Recipient's Purchase and Further Referrals

I first present my main findings on the effect of different messages on recipient's purchase decision as well as further referral behavior.

I. Effect of message design on recipient's purchases

I show the effect of message on recipient's purchase at both the sender level and the recipient level, using various specifications estimated in OLS (see Table 2). At the sender level, the outcome variable is the average number of successful referral purchases per sender. At the recipient level, the outcome variable is the recipient's binary purchase decision.

I begin by estimating a model at the sender level using only the indicator variable for each message group and not including controls. Compared to the baseline message, simply adding information about the sender's purchase status leads to a large increase in the average number of referral purchases per sender. The increase is statistically significant and economically sizable (an increase of over 15% compared to the baseline purchase rate). Interestingly, once information about the referral reward is provided in addition to information on the sender's purchase status, the increase in purchases is attenuated and the increase over control becomes insignificant. The negative incremental effect of adding referral reward information (T3-T1) is sizable and statistically significant, indicating the negative interaction effect of information about referral reward with information about the sender's purchase. This finding is consistent with previous work (Verlegh et al. 2013) on sender' credibility/motivation. Once the recipient realizes the sender may be eligible for a referral reward, she may question the credibility of the referral or infer ulterior motivations from such sharing (Tuk et al. 2009). Finally, the difference between the referral-reward-information only treatment and control is relatively small and not statistically significant. In keeping with perfect randomization, I obtain consistent results after I add a full set of controls using sender and product characteristics. Moreover, similar results hold for analysis at the recipient level (with and without controls), with error grouped at the deal level.

With the increase in recipient's purchases, the firm may incur an additional cost in the form of sender's referral reward. Thus, I examine the net profit the firm can gain by aggregating net revenue and cost from referrals at the sender level. Consistent with previous results, I find that adding information about sender's purchase leads to a significant increase in the net profit for the platform, after accounting for the cost of referral rewards.

I also run a series of robustness checks. First, my results are robust across alternative specifications at both levels, including count models at the sender level and limited dependent variable model at the recipient level. I obtain consistent results using Poisson and Negative Binomial models at the sender level and probit and logit models at the recipient level (see Appendix A, Table A1). Second, I observe shares on a wide range of deals in my sample following a long tail distribution. For some of deals, the number of senders is very small. Even though the deals are randomized into one of the four groups and the number of deals is very large in my test, it is still possible (though unlikely given the large sample size) that my estimates can be biased if some of the 'good' deals are all randomized into the same group (I define a deal as 'good' for a specific treatment if the treatment can lead to an increase in purchases for the deal). Thus, I run an OLS model with deal fixed effect and take advantage of within deal variation for my identification (Appendix A, Table A2). The results are consistent (and even more significant) after I include deal fixed effects.

II. Effect of message design on recipient's further referral

Adding information about referral rewards may increase recipient's awareness of the monetary reward and raise the likelihood of making further referrals. I observe such a response in my data (see Table 3). On average, recipients who are exposed to messages containing only the referral reward information make 68% more successful referrals after purchase, compared to recipients in the control group. Interestingly, recipients who receive the message with both pieces of information are much less likely to make further referrals. Such a decrease may be due to the concern about one's own image in further referrals (Ryu and Feick 2007). I do not observe a significant increase in further referral behaviors for recipients who are only exposed to information about the sender's purchase.

In summary, I find that a simple variation in message design can greatly enhance social contagion. On the one hand, adding information about the sender's purchase greatly increases the recipient's likelihood of purchase, with an increase of more than 15% relative to the control group. On the other hand, adding information about referral reward alone significantly increase the recipient's further referrals. Both effects are economically significant, especially considering the large volume of customer shares through the platform every day. However, adding information about sender's purchase and referral rewards at the same time dampens the positive effect on both recipient's purchase as well as recipient's further referrals.

2.7.2. What are Friends For? Mechanisms Underlying Social Contagion

Having identified the main effect at the aggregate level, I further examine *how* message design affects the effectiveness of information sharing, by exploring the heterogeneity in treatment effect on different types of deals, different types of individuals, as well as different tie strength.

Social Learning vs. Social Utility

As discussed earlier, two mechanisms – Social learning and Social utility -- may be at work in driving the increase in recipient's purchases[5]. If social learning is at work, I should see an increase in purchases for less experienced users when they observe their friend's purchase, as they may place more weight on the new information relative their own knowledge/signal. Similarly, I should see an increase in purchases for recipients who receive deals about less popular products and for recipients who receive messages about deals that are in the earlier stage of the product sales cycle. Under each of these circumstances, the recipients are likely to have less information and face more uncertainty about the product, and thus, more likely to rely on the information implicit in their friend's purchases. On the other hand, if social utility is at work, I should see an increase in purchases for recipients of 'social' products as they can gain additional social utility (local network effect) from their friends' participation.

My rich dataset enables me to construct measures for recipient experience, product popularity, and the stage of the product's sales cycle, and 'social-ness' of the product. First, using complete purchase history of each recipient from the beginning of the

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[5] Increase in conversions may also occur due to an increase in awareness/attention rather than due to the treatment (i.e., the content of the message). As noted earlier, my experiment design deactivates this channel.

platform, I am able to identify whether the recipient has experience with platform in general as well as with the specific product category. I define a recipient as experienced if she has at least one past purchase in the same product category. Second, I define product popularity based on product sales within each category. If the product sales is within the top 50 percentile of all shared deals in my experiment, then I categorize it as popular; if the product sales is within the bottom 50 percentile, I categorize it as unpopular. Third, since I observe the timing of each purchase for every product in my experiment (including purchases from non-sharing channels), I can calculate the percentage of sales that have occurred for the deal when it is shared with the recipient. I define a recipient as an early customer/purchaser if she received the share in the early part (initial 50%) of the product sales cycle. Finally, the shared deals in my sample range across eight categories and more than 100 subcategories (including restaurant, entertainment, fast food / desserts, home service, retail products, active/fitness, beauty/spa and escape at category level). I manually go over the deals in each subcategory. Based on the nature of the subcategory (whether it involves a group activity or not) and the redemption pattern (whether friends redeem the deal at the same time or not), I code and classify the category/subcategory into social vs. non-social categories/subcategories. I report the main results based on category-level coding. I also test alternative categorization for each of the above constructs using alternative cutoff points and more granular measures[6]. My results are robust across alternative definitions of each construct.

I conduct my analysis at the recipient level and interact each of the above moderating variables with the indicator of treatment group while controlling for all other factors (as specified in the empirical strategy). The empirical findings in Table 4 indicate that social learning is at work in the instances with higher uncertainty for the recipient. I find that

[6] These results are available upon request from the authors.

the effect of adding information about the sender's purchase status (T1-C) varies across the different types of individuals and products. Information about the sender's purchase has a larger and more significant effect on recipients who are less experienced, on less popular products, and on products in the earlier stages of the product sales cycle. Second, the incremental effect of information about referral rewards greatly attenuates the increase in recipient's purchase for the recipients described above, but less so for the comparison group.

On the other hand, I also find evidence that social utility also plays a role (see Table 5). The increase in purchases is higher and more significant for social products when information about friend's purchase is revealed to the recipient. This is because the recipient may enjoy additional utility from a friend's participation in the event. In other words, friends serve two important roles in my context: they serve as credible sources of information to their social connections and facilitating social learning; they also serve as companions and confer social utility for social product and events.

2.7.3. Additional Moderators in Treatment Effect: Social Tie Strength and Targeted Shares

I further explore the heterogeneity in the treatment effect, which may help me better understand the underlying mechanism at work. There are two important variables that would lead to further heterogeneity in treatment effect: social-tie strength and target-iveness of the share. Tie strength may moderate both social learning and social utility. On the one hand, the recipient can learn more from a friend with a stronger social tie, as she places more trust when observing a share from such friend (Cai 2014). On the other hand, if the shared product is a social product, the recipient may gain additional utility from consuming the product with a closer friend (Sundararajan 2007). Whether the sharing is targeted or not, may also affect the effect of information about the sender's purchase. If the share from the sender is targeted to a specific customer, then it is more likely that there is a good fit between the shared product and the customer. In such case, the recipient may already find the product attractive and the information about the friend's purchase is less informative. Thus, I may see less increase for more targeted shares.

I construct the measure for social-tie strength using the sharing history between sender and recipient since the beginning of the platform. If the historical share within a pair is reciprocal (i.e. both parties have sent and received shares from the other party), then I define the social-tie strength of the pair as strong (Granovetter 1973); otherwise the social tie strength is considered weak. I construct the target-iveness of the share based on the number of recipients in the sender's share. I choose the threshold to be two as about half of the senders share with 1 or 2 people. If there are more than two recipients, then I consider the share as non-targeted; if the share is only made to one or two recipients, then I consider it as targeted.

Table 6 and 7 illustrate the additional results on heterogeneity in treatment effect by decomposing recipients into two groups, based on the two measures discussed above. I find that the strength of the social-tie between a sender and a recipient significantly moderates the treatment effect of different message designs. Adding information about sender's purchase leads to a much higher lift in purchases for sender-recipient pairs with reciprocal social interactions ('strong tie'), compared to those pairs without reciprocal social interactions ('weak tie') (See Table 6 left panel and Table 7). The difference is more salient for social products (see Table 7). This indicates the importance of tie strength in both social learning and social utility. I also find that, adding information about the sender's purchase leads to higher lift in purchases for non-targeted shares, compared to targeted shares, providing additional evidence of social learning at work (see Table 6 right panel).

2.7.4. Welfare Implications of Message Design

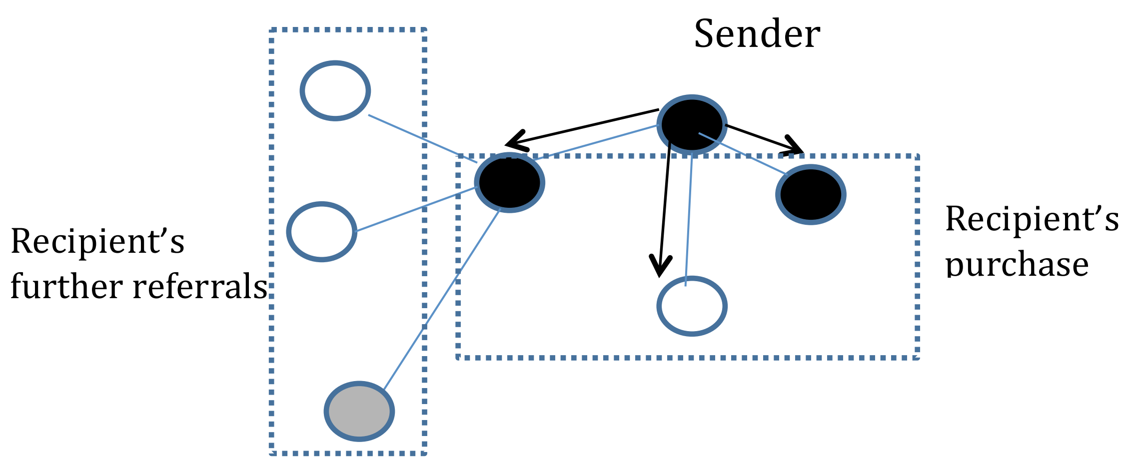
Finally, I explore the welfare implications of message design. The platform sends automated customer surveys upon customer's redemption of vouchers. The survey is simple and includes two questions: 1) thumbs-up or thumbs-down for your visits; 2) will you ever return? (yes or no). For the first question, I code a thumbs-up as 1 and a thumbs-down as 0; for the second question, I code a yes as 1 and a no as 0. The automated email survey is sent out only if the merchant has reported a customer's redemption of vouchers, or if the customer labels her voucher as used. Thus, the final data I have for the automated survey is determined by two factors: 1) the merchant's report (or a customer's self-report) of customer's redemption; 2) the response rate to the emails sent out. The final recipients who have provided feedback are slightly less than 10% of the total purchasers. The sample size in each test group is approximately the same. Table 8 illustrates the difference in customer feedback data across the four groups at the aggregate level as well as decomposed into social product vs. standalone product. I find evidence that recipients who receive message with sender's purchase information are more likely to report a positive experience (thumbs-up) and to report a willingness to return. This increase is larger for social products than for standalone products, suggesting that social utility might play an important role in determining customer experience.

2.8. Future Research

Identifying optimal design of firm-mediated message at a group level is a useful first step. With the availability of large amount of data on sender and recipient behaviors and their historical interactions, as well as the ability to process requests in real time, firms can actually personalize messages at an individual level. While personalization is a common practice in the context of firm-customer interactions, personalization of firm-mediated customer-customer social interactions is still in its infancy. I plan to further extend the current study along this direction, specifically in two ways: first, I plan to explore more heterogeneity in the data, strengthen descriptive positioning of current article ("what works best when") and emphasize its managerial contribution; second, I plan to identify optimal intervention at subgroup or even individual level, utilizing large number of covariates in the big data (on characteristics of senders, recipients, strength of ties, and products) and advanced predictive modeling approach (e.g. SVM, LASSO). I envision that in the near future when a firm gets a request of email share from a sender, it would leverage historical information to extract product characteristics, sender and recipient's purchase and interaction histories, calculate optimal content and message design, and deliver the message in real time in a personalized fashion. My ongoing work serves as a valuable proof-of-concept of this impending development

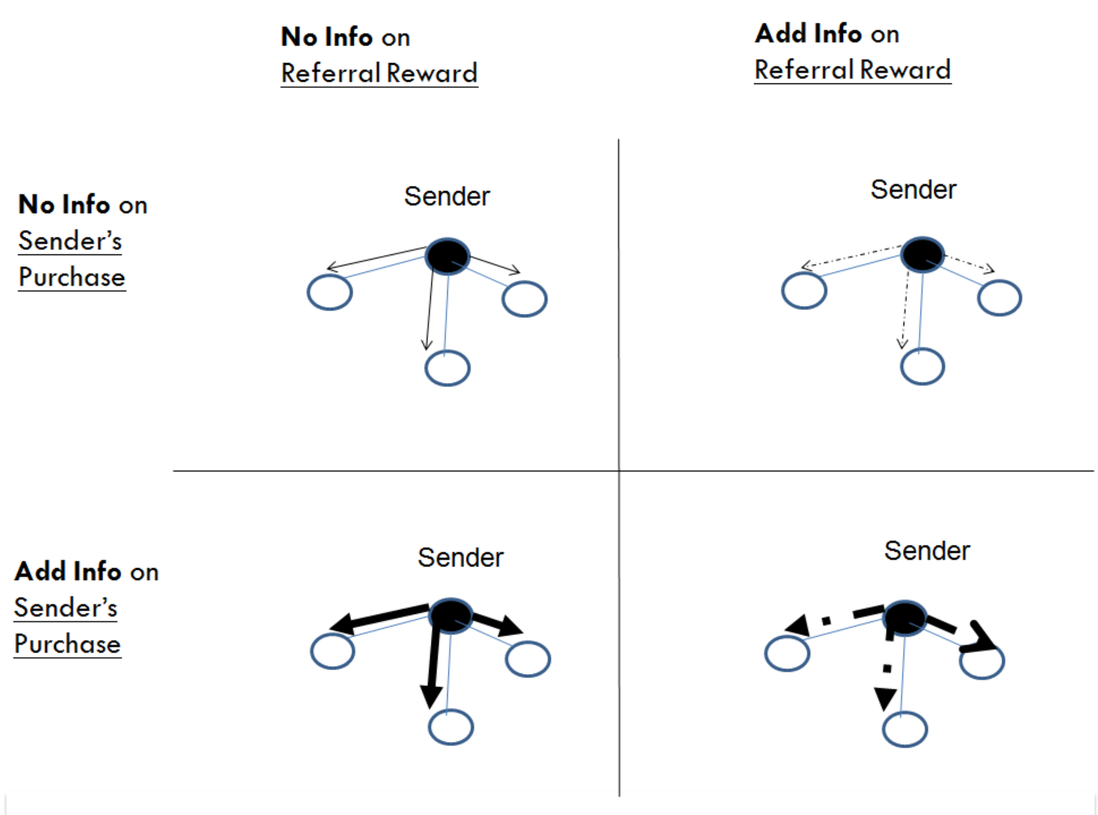
Figures and Tables for Chapter 2 (Essay 1)

Figure 1: Key social contagion outcomes under tracking: Recipient's purchase and Recipient's further referrals

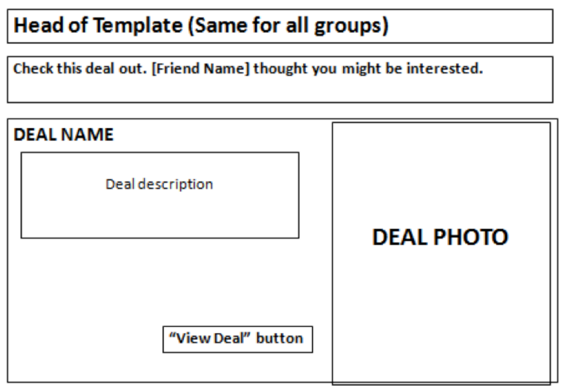


* Note: in the scenario illustrated above, two recipients out of three have purchased the deal through the sender's share. Furthermore, one recipient (the one on the left) has brought one successful referral after her own purchase.

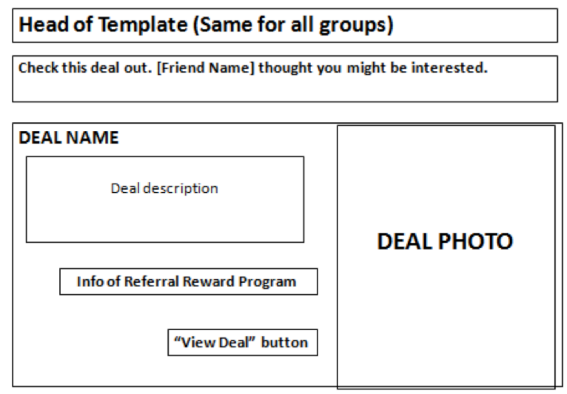
Figure 2: Experiment Design: Random assignment of Sender with one of the test messages



Figures 3: Messages used in the randomized field experiment

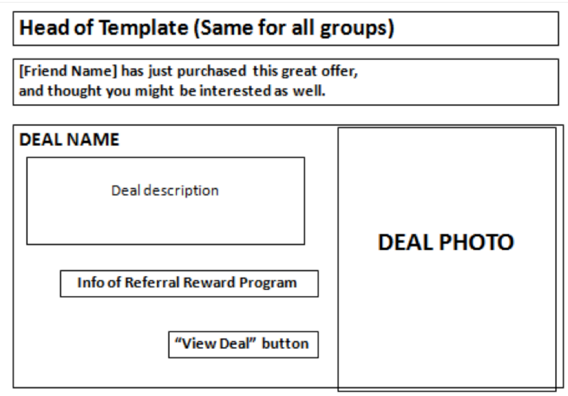


Panel A: Message Template for control group C



Panel C: Message Template for treatment T2

Panel B: Message Template for treatment T1



Panel D: Message Template for treatment T3

Figure 4: Illustration of implementation of message design experiment

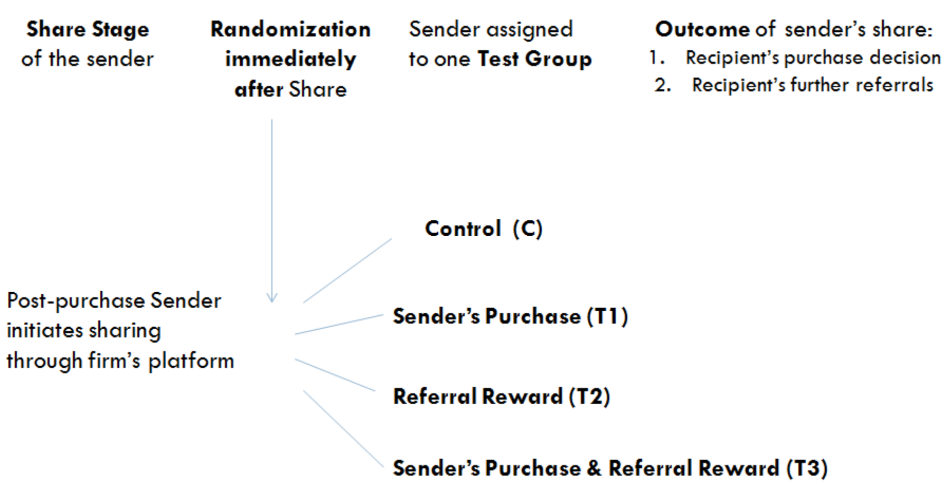


Figure 5: Overall Effect of Message Design on Recipient's Purchase and Further Referrals

Info about Referral Rewards Info about Sender's Purchase	**Invisible**	**Visible**
Invisible	Baseline (Group C)	No significant effect on recipient's purchase Increase further referrals (Group T2)
Visible	Significant increase in recipient's purchases No effect on further referrals (Group T1)	No significant effect on recipient's purchase No effect on further referrals (Group T3)

Table 1: Descriptive Statistics and Randomization Check

	Control		Treatment Group 1		Treatment Group 2		Treatment Group 3		p-value (C=T1= T2=T3)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Sender Characteristics	(N=5626)		(N=5684)		(N=5687)		(N=5643)		
Total Number of Past Purchases (before test)	0.000	9.335	-0.064	9.305	-0.155	9.115	0.180	9.488	0.269
Total Spending (before test)	0.000	458.1	3.156	471.4	-5.920	428.8	10.826	445.7	0.255
Days after Creating Account	0.000	422.2	1.276	422.4	-5.794	425.7	5.155	424.3	0.587
Shared Deal Characteristics	(N=1457)		(N=1493)		(N=1529)		(N=1492)		
Average price	0.000	123.1	1.6	120.6	-0.5	103.1	0.4	117.9	0.815
Popularity	0.000	1571.0	-34.9	1318.6	-55.3	1242.7	-20.0	1362.4	0.181
Category dummy									
Restaurant	0.000	0.391	0.004	0.394	0.009	0.398	0.004	0.395	0.722
Entertainment	0.000	0.481	-0.001	0.481	-0.016	0.477	-0.006	0.480	0.279
Fast Food/QSR	0.000	0.163	-0.003	0.154	-0.003	0.156	-0.001	0.160	0.709
Home Service	0.000	0.281	-0.003	0.276	-0.008	0.270	-0.003	0.276	0.536
Retail product	0.000	0.180	0.005	0.192	-0.001	0.177	0.005	0.191	0.197
Active/Fitness (group)	0.000	0.361	-0.009	0.353	-0.002	0.359	-0.004	0.357	0.598
Beauty & Spa	0.000	0.300	0.006	0.308	0.016	0.321	0.004	0.306	0.136
Escape	0.000	0.206	0.001	0.209	0.004	0.214	0.002	0.210	0.836
Recipient Characteristics	(N=13161)		(N=13746)		(N=13509)		(N=13548)		
Total Number of Past Purchases (before test)	0.000	6.331	-0.022	6.278	-0.094	5.928	-0.039	6.276	0.639
Total Spending (before test)	0.000	283.4	-1.649	265.6	-3.304	257.4	-3.424	255.2	0.688
Days after Creating Account	0.000	512.7	5.174	513.4	3.539	511.3	7.277	514.3	0.698
Social Tie Characteristics									
Average number of shares between a pair	0.000	0.885	0.012	0.893	-0.012	0.869	-0.013	0.876	0.165
Percentage of reciprocal tie	0.000	0.271	-0.003	0.266	-0.004	0.264	-0.003	0.265	0.621

* The figures provided are demeaned values obtained by subtracting the mean value of treatment groups from that of control group. Demeaning preserves the difference in mean value between test groups as well as the t-test (i.e. randomization check). Pairwise t-test is available upon request.

Table 2: Effect of Message Design on Purchase

Outcome	**Purchase Decision (0/1)**				**Net Revenue (Net Cost of Referral Reward)**	
Level	**Sender Level**		**Recipient Level**		**Sender Level**	
T1-C	0.0366***	0.0312***	0.0116**	0.0130***	1.489**	1.392**
T2-C	-0.00467	-0.00526	-0.00362	-0.00242	-0.208	-0.243
T3-C	0.0127	0.00837	0.00250	0.00330	1.004	0.939
Sender-level Controls						
Sender Tier 1		0.0282***		0.00585		-0.275
Sender Tier 2		0.0259**		4.61e-05		0.562
Sender Tier 3		0.0495***		0.00583		1.514
Sender Tier 4		0.0372**		-0.00242		2.108
Account length		-1.21e-05		-8.05e-06*		-0.00061
Number of Recipients		0.0648***		0.0060***		0.974***
Product-related Controls						
Product Price		0.00049***		0.000216***		0.0266
Product Popularity		-1.74e-06		-1.71e-06		5.57e-05
Category dummy		Yes		Yes		Yes
Recipient Controls						
Recipient Tier 1				0.0607***		
Recipient Tier 2				0.0885***		
Recipient Tier 3				0.115***		
Recipient Tier 4				0.133***		
Account Length				-1.01e-05***		
Social Tie Characteristics						
Reciprocity in shares				-0.00459		
Total past shares				-0.00172		
Observations	22,640	22,640	53,964	53,964	22,640	22,640
p-value (T3-T1)	0.0448	0.0484	0.0643	0.0413	0.631	0.645

* Sender and recipient tier is defined based on the number of total past purchases. Customers in higher tiers have made more purchases.

Table 3: Effect of Message Design on Successful Follow-up Referrals

Outcome	Number of Successful Referrals			
Level	Sender level		Recipient level	
T1-C	0.0376	0.0315	0.00328	-0.00167
T2-C	0.0683*	0.0717*	0.0414**	0.0404*
T3-C	0.00767	0.00338	-0.00198	-0.00146
Sender controls	No	Yes	No	Yes
Product controls	No	Yes	No	Yes
Recipient controls	No	No	No	Yes
Social tie controls	No	No	No	Yes

Table 4: Social Learning

	Recipient Experience		Product Popularity		Late Stage in Product Lifecycle	
	Only adding information about sender's purchase (T1-C)					
Treatment Effect for Subgroup						
More	0.00282	0.00371	0.00322	0.00529	0.00807**	0.00922
Less	0.0114***	0.0126**	0.0182***	0.0197***	0.0257***	0.0269***
Coefficient for Moderator	0.104***	0.133***	0.00523	0.00461	0.0387***	0.0433***
Sender controls	No	Yes	No	Yes	No	Yes
Product controls	No	Yes	No	Yes	No	Yes
Recipient controls	No	Yes	No	Yes	No	Yes
Social tie controls	No	Yes	No	Yes	No	Yes
	Incremental effect of adding information about sharing reward (T3-T1)					
More	0.0207*	0.0181	0.00441	0.00276	-0.00717*	-0.00792
Less	-0.0126***	-0.0118**	-0.0193***	-0.0172***	-0.0179**	-0.0173*
Coefficient for Moderator	0.0952***	0.0991***	-0.00970*	-0.00770	0.0211***	0.0254***
Sender controls	No	Yes	No	Yes	No	Yes
Product controls	No	Yes	No	Yes	No	Yes
Recipient controls	No	Yes	No	Yes	No	Yes
Social tie controls	No	Yes	No	Yes	No	Yes

Table 5: Social Utility (Local Network Effects)

Information about Sender's Purchase Status (T1-C)		
Treatment for Social Product	0.0172***	0.0171**
Treatment for Non-social Product Category	0.00588	0.00813
Indicator of Social Category	0.0308***	0.0380***
Sender controls	No	Yes
Product controls	No	Yes
Recipient controls	No	Yes
Social tie controls	No	Yes
Observations	26,907	26,907
p-value (T3-T1)	0.145	0.145

Table 6: Social Learning (Moderated by Tie Strength and Share Targetiveness)

		Tie Strength		Targetiveness	
	Recipient Experience	Weak Tie	Strong Tie	Targeted	Non-targeted
Information about Sender's Purchase Status (T1-C)	More	-0.0175	0.0411*	0.00451	-9.88e-05
	Less	0.0113***	0.0618**	0.00437	0.0168***

* A full set of controls has been applied.

Table 7: Social Utility (Moderated by Tie Strength)

		Social Product	
		No	Yes
Information about Sender's Purchase Status (T1-C)	**Weak Tie**	0.00534	0.0139**
	Strong Tie	0.0300*	0.0612***
Information about Sender's Purchase Status & Reward for Sharing minus Information about Sender's purchase status (T3-T1)	**Weak Tie**	-0.00787	-0.0144**
	Strong Tie	0.00720	0.0369*

* A full set of control has been applied.

Table 8: Customer Feedback After Consuming the Deal

Outcome A:	**Thumbs-Up**		
	All	**Stand-Alone Product**	**Social Product**
T1-C	0.0845*	0.0449	0.119*
T2-C	0.0535	0.0274	0.0696
T3-C	0.0185	-0.0533	0.0864
Outcome B:	**Will Return**		
	All	**Stand-Alone Product**	**Social Product**
T1-C	0.0843*	0.0686	0.111
T2-C	0.0907*	0.0457	0.176*
T3-C	0.0139	0.00364	0.0357
Observations	314	203	111

Table A1: Alternative Specification for Main Effect on Purchase

	Sender level			
	Poisson Model		Negative Binomal	
T1-C	0.134***	0.121***	0.134***	0.123***
T2-C	-0.0185	-0.0211	-0.0185	-0.0128
T3-C	0.0486	0.0255	0.0486	0.0331
Marginal effects				
T1-C	0.0357***	0.0317***	0.0357***	0.0368***
T2-C	-0.00491	-0.00571	-0.00491	-0.00401
T3-C	0.0129	0.0645	0.0129	0.0923
Controls	No	Yes	No	Yes

	Recipient level			
	Probit		Logit	
T1-C	0.0598**	0.0692***	0.114**	0.135***
T2-C	-0.0196	-0.0153	-0.0379	-0.0241
T3-C	0.0133	0.0197	0.0255	0.0417
Marginal effects				
T1-C	0.0115***	0.0124***	0.0115***	0.0122***
T2-C	-0.00370	-0.00271	-0.00372	-0.00218
T3-C	0.00252	0.00264	0.00253	0.00291
Controls	No	Yes	No	Yes

Table A2: Robustness Check on Main Effect with Deal Fixed Effect

Outcome	**Number of Successful Referrals**			
Level	**Sender level**		**Recipient level**	
T1-C	0.0424***	0.0375***	0.0118***	0.0136***
T2-C	-0.000508	-0.000839	-0.00282	-0.00221
T3-C	0.00696	0.00420	-0.00159	0.000116
Sender controls	No	Yes	No	Yes
Product controls	No	Yes	No	Yes
Recipient controls	No	No	No	Yes
Social tie controls	No	No	No	Yes
Observations	22,640	22,640	53,964	53,964
p-value (T3-T1)	0.00876	0.0119	0.00223	0.00200

Appendix 1: Controlling Spillover

Similar to previous random trial studies in networked environments (Aral and Walker 2011, Bapna and Umyarov 2014), my intervention may also face potential spillover problems. As discussed in the experiment design section, I choose the random assignment to be the same within each sender's local network. Thus, any observed or unobserved spillovers (e.g. online or offline communication between two recipients about the sender's purchase status or referral reward) is of less concern under my randomization approach.

Nonetheless, there are two potential spillover channels that may affect my analysis. First, some recipients may receive shares for the same product from multiple senders (either in different or the same treatment group). In the former case, the recipient is contaminated as the she is exposed to different messages. In the latter case, there is an attribution problem as it is not reasonable to completely ascribe recipient's potential purchase to any one of the sender. Following similar procedures to previous studies (Aral and Walker 2011a, Bapna and Umyarov 2014), I exclude those recipients who are exposed to shares from multiple friends, which comprises a very small subset of my sample.

Another potential spillover channel which is unique to my context is that some recipients may receive shares of multiple products during my experiment as it runs for a short period of time. The share may come from either the same sender or a different sender and may either be in the same treatment or in a different treatment group. I exclude all such shares except the message for first product. It has a negligible impact on the size of my sample.

When a sender shares a different deal after the first time, she is again randomly assigned to one of the four test groups. However, I also exclude such senders (as they comprise a very small fraction of all senders) to maintain consistency in my empirical analysis, and as the sender may self-select into sharing again based on referral outcomes in the previous share.

Finally, I want to highlight that such exclusion may be very unlikely to bias my results as: 1) the dropped sample is very small (<4% of my sample); 2) the randomization on the message is orthogonal to the sharing pattern. However, it is possible that such exclusion may slightly reduce the heterogeneity in my sample.

Appendix 2: Optimal Message Design

Tradeoff between increasing purchases or further referrals

I provide a simplified analysis on the tradeoff between increase in purchases and increase in further referrals. The goal is to examine under what circumstances the firm should encourage more purchases rather than further referrals, and vice versa.

Assume there are N senders and on average each sender shares with M people. Let the baseline adoption rate be c and the number of successful further referrals be s. I focus on the further referrals from recipient who have made the purchase, as referrals from recipients who have not made the purchase are extremely rare in my case and probably in many other online shopping contexts. Ignoring the spillover (i.e. recipients who receives shares from more than one sender) which is relative small and also orthogonal to my randomized treatment, I can derive the total number of purchases from sharing within the first and second degree of the sender's social network as:

$$N*M*c + N*M*c*s$$

Now consider there are two treatment groups (i=1,2) in the message design experiment; the increase in baseline adoption rate and number of successful further referrals is Δc_i and Δs_i respectively (all in absolute magnitude instead of percentage). Thus, the total number of purchases from sharing for the two treatment groups is:

$$N*M*(c+\Delta c_i) + N*M* (c+\Delta c_i)* (s+\Delta s_i)$$

Define Δc_1-Δc_2=Δc, Δs_1-Δs_2=Δs; Assume Δc_1>Δc_2 and Δs_1<Δs_2 (i.e. treatment 1 results in more purchases and treatment 2 in more referrals by the recipients), thus the difference in the two treatment groups are:

$$\{N*M*(c+\Delta c_i) + N*M* (c+\Delta c_i)* (s+\Delta s_i)\} - \{N*M*(c+\Delta c_i) + N*M* (c+\Delta c_i)* (s+\Delta s_i)\}$$
$$= N*M* (\Delta c_1-\Delta c_2) + N*M*(\Delta c_1-\Delta c_2)*(s+\Delta s_1) - N*M*(c+\Delta c_2)*(\Delta s_2-\Delta s_1)$$
$$= N*M* \{\Delta c+\Delta c*(s+\Delta s_1) - (c+\Delta c_2)* \Delta s\}$$

The three terms represent the key tradeoffs in the comparison and correspond to the two outcomes illustrated in Figure 1. The first and second term indicates the difference in increased purchases from the new adopters as well as the second degree of those new adopters. The third term mainly indicates the difference in increased further referrals from existing adopters. The condition that treatment 1 brings more purchases than treatment 2 is given by,

$$N*M* \{\Delta c+\Delta c*(s+\Delta s_1) - (c+\Delta c_2)* \Delta s\} > 0$$

$$i.e., \qquad \frac{\Delta c}{\Delta s} > \frac{c+\Delta c_2}{1+(s+\Delta s_1)}$$

In my case, $\Delta s_1 \sim 0$ and $\Delta c_2 \sim 0$ (i.e. treatment 1 increases purchases but does not increase further referrals, treatment 2 increases further referrals but not purchases). Thus the firm should pursue Treatment 1 to encourage more purchases if:

$$\frac{\Delta c}{\Delta s} > \frac{c}{1+s}$$

In other words, the firm should pursue Treatment 1

1) (right hand side) when baseline adoption rate (i.e. number of existing customers) is relatively low and the baseline number of successful further referrals is relatively high.

2) (left hand side) when the difference in increased adoption rate is relative high compared to the difference in increased further referrals.

The intuition behind the comparison is very simple: when baseline adoption rate is relatively low, then the increase in further referrals from existing customer is small; thus there is no large gain from encouraging more referrals. When the baseline further referrals is relatively high, one additional first degree adopter can bring more second degree adopters; the high social multiplier effect makes an increase in baseline adoption rate even more desirable. Thus, both cases favor more purchases over more additional referrals.

In my case, the baseline adoption rate is not high (compared to online games or content consumption) as it is costly for the recipients. Thus, the firm in my context (and probably in many other similar online shopping contexts) should encourage an increase in purchases by providing information about the sender's purchase rather than an increase in further referrals by displaying information about the referral reward.

Chapter 3:

Essay 2 -- Monetizing Sharing Traffic through Incentive Design: Evidence from a Randomized Field Experiment

3.1. Introduction

Online social sharing platforms such as Facebook, Pinterest, Groupon and LivingSocial have dramatically increased the ability of customers to share product information with their social connections. A huge volume of product information is shared daily through those digital channels. While the sharing of a product indicates the purchase intent of either the sender or the recipient, or both, most of such 'shares' do not lead to successful conversions of either the sender or the recipient[7]. This presents an interesting opportunity to the firm. With increasing availability of data on sharing among peers, as well as the ability to process such data in real time, firms can now monetize the sharing traffic by targeting customers in the share with promotions. Despite its huge volume and growing importance, no study has investigated how firms can take advantage of such online sharing traffic and convert senders and recipients involved in the shares. My paper aims to fill this gap by examining whether and how firms can engage customers in information sharing, through the design of novel incentives.

Specifically, this study has three objectives. The first objective is to test the effectiveness of different incentive designs in converting sharing traffic. Sharing traffic is similar to website and online search traffic to the extent that such sharing is reflective of the sender's own interest in the shared product. However, sharing behavior also

7 In my context, the number of senders exceeds five million but only less than 10% of them ever purchased the shared product; even a smaller percent of share recipients ever made a purchase. The opportunity size in engaging those customers is huge. Even a marginal increase in conversion rate would lead to huge increase in net revenue.

fundamentally differs from online browsing and search behavior in two key aspects – first, a share could indicate the interest of the recipient, or the group (the sender as well as the recipient), rather than just the interest of a single customer for that particular deal. Thus the firm should look beyond the focal customer (i.e. sender) and take into account the purchase decision of her social connections when designing the targeting strategy; second, a share reveals sender's strong willingness to share information with friends. Thus the firm can take advantage of this behavior trait and leverage the sender as an influencer to engage the recipients. Those two unique features indicate that firms should *customize* their behavioral targeting strategy for sharing behavior. Specifically, firms can target the sender with novel incentives: not only to improve her own adoption, but also to leverage her to influence and engage the recipients. Iconduct a randomized field experiment to empirically test the effect of different incentive designs on these two outcomes.

The second objective of the study is to gain insights on the sender's motives in sharing. The act of sharing (albeit, information) could reflect the sender's other-regarding motives, or sender's group-regarding motives, in addition to her self-regarding motives. Despite the prevalence and importance of all three types of motives (List 2007, Chen et al. 2009), there are no studies that have investigated them in the same framework. Taking advantage of the unique context of online information sharing, my study seeks to disentangle the three motives using a randomized field experiment. Specifically, the sender's response to different incentive designs can reveal the self-regarding, other-regarding, or group-regarding motives underlying her sharing behavior.

The final objective of my study is to combine the first two objectives and customize the targeting strategy (i.e. incentive design) at individual level based on the sender's sharing motive. While all three motives in sharing can be beneficial to the firm, they have very different implications for the firm's optimal targeting strategies. Understanding the underlying motivations of a share can enable the firm to identify appropriate incentives in individual level targeting.

To achieve the above objectives, I design and implement a large-scale randomized field experiment in collaboration with a leading daily deal platform to identify the causal effect of incentive design in monetizing the sharing traffic and to tease out the underlying motives of the sender. Specifically, I target the sender with incentives (single-use promotional-codes or promo-codes for short) aimed at converting the sender, the recipients, or the group (the sender and the recipients). I focus on two dimensions in my incentive design – the number of promo codes available to the sender and whether these promo codes can be shared. By varying the two dimensions, I create four versions of emails – (i) a reminder email with no promo-code (T1), (ii) an email containing one promo-code for the sender (T2), (iii) an email containing one promo-code that can either be used either by the sender or be shared with her friends (T3), (iv) an email containing two promo-codes, one for use by the sender and another to be shared with her friends (T4). By allowing the sender to share the promo-code with her connections (in T3), I essentially create a tension in the sender's decision. On the one hand, the sender can use the code and enjoy the monetary benefits herself. On the other hand, the sender can share the promo-code with her social connections and gain (non-material payoff) utility from her friend's consumption. Thus the sender's decision resembles a classical dictator game in which one participant is endowed with a fixed amount of money and can decide how much to allocate to others.

I choose participants in my experiment to be senders who had shared deals with friends the previous day but did not purchase themselves. I randomly assigned eligible senders into one of the five test groups (See Figure 2), and target the senders in treatment groups with different emails. The randomization allows me to identify the impact of incentive design on sender's purchase as well as further referral behaviors with recipients and other friends (See Figure 1). The experiment was successfully implemented in late 2014. I find evidence that the incentive structure has a significant impact on both purchase and referral decisions of the sender, but in different ways. Specifically, I find that the provision of one (non-shareable) promo-code for the sender significantly increases her probability of purchasing the shared product; the increase can be explained by the additional usage of promo-codes. I find the promo codes are most likely to be used when the sender has purchased deals before in the same category as the shared deal – indicating that the self-regarding motive at work. I also find that the provision of one shareable promo-code (T3) to the sender, leads to an increase in sender's purchases but to a lesser degree than the case (T2) with a non-shareable promo-code; however, it leads to a significant increase in referral purchases by recipients. I find that the sender is less likely to use the promo code herself compared to T2, but is more likely to refer friends who purchase the deal using the shared promo-code. An established stream of literature in psychology and economics has found consistent evidence in other context that people care not only about their own material payoff but also about others' welfare, due to altruism, fairness, or reciprocity. My findings from T3 are consistent with this central insight. Finally, the provision of two promo-codes (T4) leads to an increase in both the sender's purchases as well as in referral purchases; however, there is a significant increase in group purchases (or purchases by both the sender and the recipient). The use of two promo-codes reveals the group-regarding motive at work. I find that the incentive is especially effective for the purchase of social products (such as tickets to social events) that are typically characterized by a positive social network effect with group consumption dominating stand-alone purchase of the deal.

The results of my field experiment provide practical implications for firms seeking to monetize sharing traffic. At the aggregate level, the firm can adopt the optimal incentive design – one shareable code – as suggested by my experiment results. However, the firm can further customize targeting strategies based on the sender's sharing motive. As in other contexts such as channel-based advertising (e.g. search ads for specific keyword, display ads on specific web page), the sender involved in sharing also self-selects into the sharing process before they are targeted. Thus, the effect of the targeting may critically depend on the motivation of the senders who share information with her social connections at the first place. My results highlight how the effectiveness of incentive design depends on the underlying motives of the sender sharing the deal. In the case of a self-regarding motive, providing incentives targeted at the sender's interest categories as reflected in her historical purchases can prove to be effective. On the other hand, if the sender's sharing is driven by other-regarding motives, then she is less likely to respond to non-shareable promo-codes but is more likely to respond to the shareable promo-codes by spreading the influence to her friends. Under such circumstances the firm could also benefit from providing incentives to the recipients. Finally, in the case of social events where senders and recipients are likely to benefit from joint consumption, the firm should provide incentives for both the sender and recipient to promote joint purchase.

Besides its direct managerial implications, the study also helps build our theoretical understanding of information sharing -- especially the motives that drive sharing. As noted earlier, understanding the antecedences of pre-purchase sharing is hard, as the action is driven by a combination of complex motives (i.e. self-regarding, other-regarding, or group-regarding). The unobserved motives may further affect the consequence of share, i.e. the sender's and recipient's adoption decisions. Thus, analysis of pre-purchase sharing behavior using secondary data may suffer from strong endogeneity problems. My field experiment helps address this issue. Senders are randomly assigned into one of the five test groups after they initiate the pre-purchase share organically. The exogenous variation created by randomization helps reveal the underlying motives at work in pre-purchase sharing. My field experiment also offers clear evidence on whether people share information with others because of altruism. Previous studies on word-of-mouth has proposed multiple psychological drivers for information sharing, including self-enhancement (Dichter 1966, Wojnicki and Godes 2011), emotion (Berger and Milkman 2012), and accessibility (Berger and Schwartz 2011). While few studies (Sundaram, et al. 1998) have suggested altruism or helping others as a potential driver, there has been no definitive evidence. In contrast, the comparison between T2 and T3 in my experiment design is especially informative on this point. By simply allowing the sender to share the promo-code (in T3), the experiment essentially creates a tension in sender's decision-making process. Since the promo-code can only be used once, the sender now needs to choose whether to keep the code for herself or share it with her friends. This could potentially lead to a tradeoff between the sender's own purchases and the purchases from her friends. I indeed see evidence of such a tradeoff in my results. In summary, my study is among the first to study how firms could distinguish between different sharing motives and customize the design of targeting strategies accordingly.

3.2. Related Literature

My study is closely related three streams of research: first, my study joins a large stream of literature on behavioral targeting based on online browsing and search behaviors (Lambert and Tucker 2013, Ghose and Yang 2009). Similar to those in search and website traffic, customers in sharing traffic reveals precious purchase intent and are valuable for targeting. Despite its large volume and growing importance, no study has provided guidelines on how to monetize such sharing traffic. I study a novel type of behavioral targeting based on sharing behavior.

My study also complements the network intervention literature (Hill et.al. 2006) by using real time data on sharing traffic to target and influence customers. Rather than focusing on 'who to target', I examine 'how to target' customers through the design of new incentive schemes. Previous targeting strategies (Lambert and Tucker 2013), including those used in social advertising (Agarwal and Hosanagar 2014), are designed to engage individual customers. In the context of sharing, individuals beyond the focal customer may have strong purchase interest. My study shows that novel incentives, designed to engage customers and their friends, can be powerful in driving both customer's own purchase as well as further referrals. Under appropriate incentives, social influence can be spread even without sender's own adoption. In this way, my study proposes a new type of network intervention to inject social influence into the network.

Finally, my study complements an emerging stream of literature that investigates the underlying motivation that drives information sharing. A large stream of literature has studied the tension between self-regarding preference and other-regarding preferences in individual decision making, using lab experiments (List 2007, Kahneman et.al. 1986), field experiments (DellaVigna et.al. 2012) and observational data (Lactera et.al. 2011). The literature finds that individuals care not only about their own material payoff, but also other's welfare, at least to some extent (e.g. in the classical dictator game, more than 20% of the participants split their benefits with the other participant). In parallel, an emerging literature examines group-regarding preferences and other-regarding motives (Duell 2015, Kranton et.al. 2013, Chen et.al. 2009). They find that individuals have more care and less envy towards other individuals within the group than outside the group (Chen et.al. 2009); they are also more likely to take destructive action towards out-of-group member. However, despite the importance of understanding the underlying motivations of the sender who shares, it is very difficult to tease out these three motivations using secondary data. My field experiment helps address the endogeneity problems and provides additional insights.

3.3. Research Context

In collaboration with a leading online daily-deal platform, I design and implement a randomized field experiment to study the causal impact of incentive design on sender's purchase and further referral behaviors. The platform offers a wide range of daily deals for local services and standard products at a high discount and has a large customer base.

On each deal page on the firm's website, the platform provides channels through which customers (senders) can share these deals with their social connections. Customers (senders) can share deals both before and after purchase by clicking specific channel buttons which are prominently displayed. The current experiment focuses on the pre-purchase sharing. Every day, a large volume of pre-purchase shares are made by customers through different sharing channels on the platform; but only a small percentage of senders in such share finally purchase the shared product. The platform observes the sender, the recipients, as well as the shared product, for every share through the platform; and can target email promotions at any time after observing such sharing.

3.4. Experiment Design

My experiment focuses on senders who had shared deals with friends the previous day but did not end up purchasing the shared deal themselves[8]. I randomly assign eligible senders into one of the five test groups (See Figure 2), and target the senders in treatment groups with different emails. By varying the number of promo-codes available to the sender as well as whether the promo-code can be shared or not, I create four versions of emails, as follows:

Control group: No email

Treatment 1 (**T1**): Email with reminder to the sender to purchase the deal she just shared

Treatment 2 (**T2**): Email with one 15% promo-code for the sender to purchase the shared deal

[8] I choose one day as the time lag after based on historical data. Most senders purchase the deal within few hours.

Treatment 3 (**T3**): Email with one 15% promo-code (sender can either use it herself or pass on the savings to a friend)

Treatment 4 (**T4**): Email with two 15% promo-codes (one for the sender & one that can be shared with a friend)

The emails are sent out once a day at the same time. Each user on the platform is eligible to receive the email at most once during the test period. The randomization happens after the sender's share and thus, incentives in the email are completely orthogonal to the sender's sharing behavior. Any difference in the sender's purchase and referral behaviors can therefore, be directly attributed to the difference in the received incentives. Using the experiment design, I seek to identify the impact of incentive design on sender's purchase as well as referral behaviors. Specifically, I focus on two key outcomes in the experiment: 1) sender's purchase; 2) sender's further referrals. The first outcome represents the conversion of the focal customer and the second outcome shows whether the influence has spread beyond the customers under targeting.

3.5. Data

The randomized field experiment has been run on the platform for a period of time and I am able to collect a large and random sample including more than 20000 unique senders (i.e. more than 4000 senders in each test group). The number of recipients who are exposed exceeds 25000. The data for my study comes from customer- to-customer shares/referrals through the platform. For every firm-mediated email share, I record the unique hashed identifier of the sender (customer ID), the recipient (hashed email address), the shared deal, as well as the assigned test group. I record the purchase status of the sender (pre- or post-purchase share), the number of recipients she specifies in the batch of sent messages, the timestamp of share. Finally, the final purchase status of the sender for her successful referrals is also recorded. I further augment the above main dataset with the historical data on sender and recipient's purchase history before experiment as well as price and subcategory of deals. The resulting dataset enables me to analyze the impact of incentive design at a granular level (i.e. heterogeneous treatment effect or moderating effect of sender and product characteristics)

3.6. Empirical Results

I first check the validity of my randomization. In table 1 I provide the breakdown of major covariates in the five groups. As shown in the results, there is no detectable variation across groups in sender characteristics (number of past purchases, total past spending, length of accounts) and shared deal characteristics (deal price and deal category dummies). The t-tests on these variables across groups are insignificant at the conventional level. The well-balanced sample indicates that my randomization works.

I find evidence that all incentive schemes have a significant impact on both purchase and referral decisions of the sender, but in a different ways. Specifically, I find i) the incentive with one (non-shareable) code for the sender significantly increase her probability of purchasing the shared product and the increase can be explained by the additional usage of promo codes; ii) the incentive that allows sharing of the code (T3) results in lower increase in sender's purchases (as compared to T2), but further motivates senders to serve as influencers for the firm and leads to significantly more referrals. In fact, most of such referrals are brought by senders who did not purchase the shared deals themselves; iii) the incentive with two codes leads to increases in both the sender's purchase as well as referrals, and works best for social products. I present the detailed results of my field experiment in the following sections..

The Effect of Incentive Design at Aggregate Level

I first present main findings using linear model without controls (linear probability model for sender's purchase, OLS model for sender's referrals, see Table 2, 3 and 4). The results are robust under alternative models (probit/logit for sender's purchase and count model for sender's referrals), as well as with controls, with little difference in the magnitude of treatment effects.

1) Effect of non-shareable incentive on sender's purchase, T2: I find that the reminder message alone has no significant impact on sender's purchase. However, once the incentive is added there is a large and significant increase in the sender's purchase. The relative increase over control group is more than 60%. The increase is sizable even after taking into account the cost of the promo codes. This increase suggests that firms can monetize sharing traffic with promotions and self-regarding preference is important in driving sender's purchase.

2) Effect of shareable incentive on sender's purchase and referrals, T3: Interestingly, once the incentive (i.e., one promo-code) is allowed to be shared, the effect on the sender's purchase is greatly attenuated and the increase over control becomes less significant. In parallel, there is a significant increase in sender's further referrals (Table 2). The decrease in sender's own purchase, combined with the increase in sender's referrals, provides strong evidence that senders have other-regarding preferences and would share the code with friends even at the cost of their own purchase. In a complementary analysis, I also find that senders under shareable incentives are more likely to make follow-up shares through the platform

3) Effect of two codes on sender's purchase and referrals, T4: Finally, when there are two promo-codes in the email, both the sender's purchase and referrals increase.

However, detailed examination (outlined in next subsection) shows that the increase is mainly driven by group regarding preferences.

In summary, firms can convert senders and recipients in sharing traffic through incentive design. On average, the sender under the incentive treatment generates more purchases and referrals. This effect is economically significant considering the large number of customers who share through the platform. Detailed calculation on the net revenue (based on sender's purchase plus sender's referrals minus the promo code cost) shows that the incentive design with one shareable promo code is most effective in increasing firm's profits.

Exploring Underlying Mechanisms Using Heterogeneity in the Data

Having identified the main effect at aggregate level, I further look into my data to untangle the motives underlying sender's sharing. I first report two heterogeneities in the treatment effect, based on the sender's purchase history as well as the recipient's purchase history. Specifically, I construct a continuous variable capturing the 'alignment' between the shared deal and the customer's revealed preference. I do it in two steps: first, I build a category-level preference vector capturing customer's historical purchases in each category and normalize the category-specific count using the total number of purchases; second, I represent the shared deal using a category-level dummy vector and calculate its product with the above preference vector. Thus, the more the customer has purchased deals in the same category as the shared deal before, the higher this variable will be. A customer who always bought deals in the same category as the shared deal would have a preference for shared deal with value 1 (and a customer who never bought deals in the same category as the shared deal would have preference value 0). I run the same set of linear models after interacting the preference variable with the treatment dummies and adding all corresponding controls (see results in Table 5).

The results confirm that senders share with different underlying motives. Those senders with a strong preference on the shared deal (self-regarding) are more likely to make purchases themselves and are much less likely to make referrals. Those senders who share with recipients with a strong preference on the shared deal (other-regarding) are more likely to make referrals. The magnitude of the interaction terms is also significant from an economic perspective.

I further examine *how* incentive design affects the sender's group purchase decision, by i) decomposing the outcome (total number of referrals) into specific scenarios ("referral only" and "both referral and purchase"); and ii) by exploring the heterogeneity in treatment effect on different types of deals. The shared deals in my sample range across more than 40 subcategories. I manually classify the subcategories into social product (e.g. group events) and standalone product (e.g. retail product), and run analysis on the two types of products separately.

The empirical findings in table 3 show that the increase the sender's referrals under shareable incentive are largely attributable to the "sender making only referrals but no purchases herself". In contrast, the increase in sender's referrals in T4 is coming from co-purchases, i.e. sender makes both purchases and referrals. Detailed examination of incentive on shares for social products vs. standalone products (table 4) shows that group incentive works best for social products that require group participation. The finding confirms my hypotheses that group regarding preference dominates customers' sharing of social products.

Customizing Incentive Design Based on the Sharing Motives of the Sender

My results show that the firm can customize the incentive design based on the underlying motives of the sender sharing the deal. Such motive can be inferred based on sender and recipient's purchase history. In the case of a self-regarding motive, providing incentives targeted at the sender's interest categories as reflected in her historical purchases can prove to be effective. On the other hand, if the sender's sharing is driven by other-regarding motives, then she is less likely to respond to non-shareable promo-code but is more likely to respond to the shareable promo-code by spreading the influence to her friends. Under such circumstances the firm could also benefit from providing incentives to the recipients. Finally, in the case of social events where senders and recipients are likely to benefit from joint consumption, the firm should provide incentives for both the sender and recipient to promote joint purchase.

3.7. Discussion

With the explosion of online social platforms and the availability of data, there is an increased desire to improve our understanding of online sharing. As noted by Watts (2012), while "no one doubts that influence is an important cause of correlated behavior, it is surprisingly hard to prove it". Watts (2012) goes on to note that while researchers have recently conducted field experiments on social platforms such as Facebook and Twitter to track the diffusion of individual pieces of content over interpersonal networks on a massive scale, these studies of retweets and likes are relatively trivial actions, and highlights the need to execute studies of this type for more consequential behaviors such as shopping. My study is among the first to answer this call by reporting on the results of a large-scale randomized field experiment (with thousands of real transactions) to untangle the underlying motives behind sharing and uncover the causal impact of incentives on the purchase and referral behaviors of individuals.

Distinguishing between these underlying motives of sharing is not only important from a theoretical perspective but also from a practical perspective. If self-regarding behavior is the underlying motive, then the firm can design incentives and promotional strategies targeted at the sender based on her historic purchase patterns to encourage adoption. On the other hand, if other-regarding motives are at work, then the firm can design shareable incentives as well as better target the recipients rather than the senders. Finally, in the case of group-regarding behaviors, the incentives and promotions can focus on social-products such as tickets to events and games that lend themselves to joint consumption.

With the availability of large amount of data on sender and recipient behaviors and their historical interactions, as well as the ability to process requests in real time, firms can actually personalize incentives at an individual level. Ongoing work examines various moderators to shed light on the variations in treatment effect for different types of senders, recipients, strength of ties, and product categories. I envision that in the near future when a firm gets a request of share from a sender, it would leverage historical information to extract product characteristics, sender and recipient's purchase and interaction histories, calculate optimal incentive design, and deliver them in real time in a personalized fashion. My work serves as a valuable proof-of-concept of this impending development.

In conclusion, my study represents one of the first large-scale field experiments to understand the causal role of incentive design on converting customers in sharing traffic. My study not only contributes to our understanding of the motives behind online sharing, but my findings also provide valuable guidelines for firms seeking to monetize such online social interactions through incentive design. The quantitative estimates and qualitative understanding gained from this series of studies can guide the optimal design of incentives for improving the targeting based on sharing. More importantly, targeting sharing traffic through incentive design is complementary to other social marketing approaches such as targeting influencers (Manchanda et al. 2008), network seeding (Hinz et al. 2011), viral product design (Aral and Walker 2011), viral content design (Berger and Milkman 2012), and referral programs (Schmitt et al. 2011), among others. It would be valuable to examine how incentive designs complements these traditional approaches. I hope that my study serves as a first step in that direction

Figures and Tables for Chapter 3 (Essay 2)

Figure 1: Key Outcome of Interest
a) Sender's purchase;
b) & c) Sender's follow-up referrals

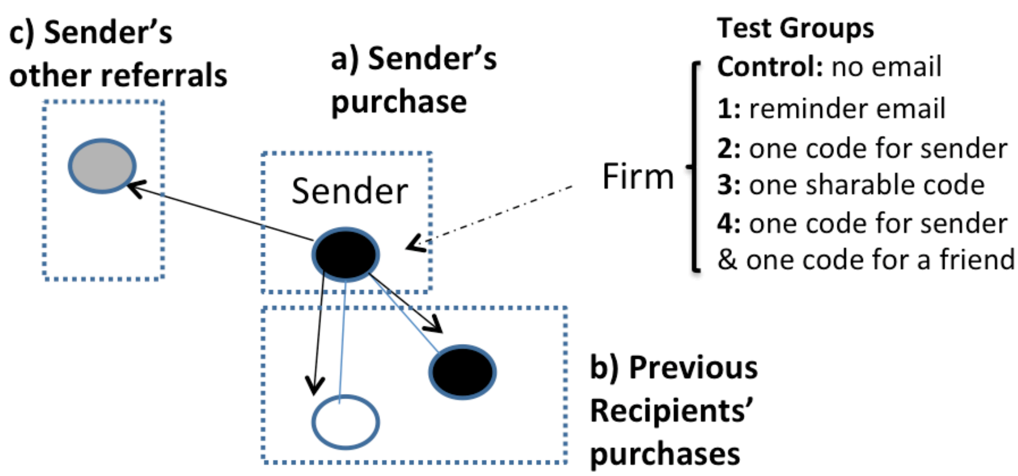


Figure 2: Experiment Design

Control group: No Message
Treatment Groups: Firm sends an automated email with different incentive designs

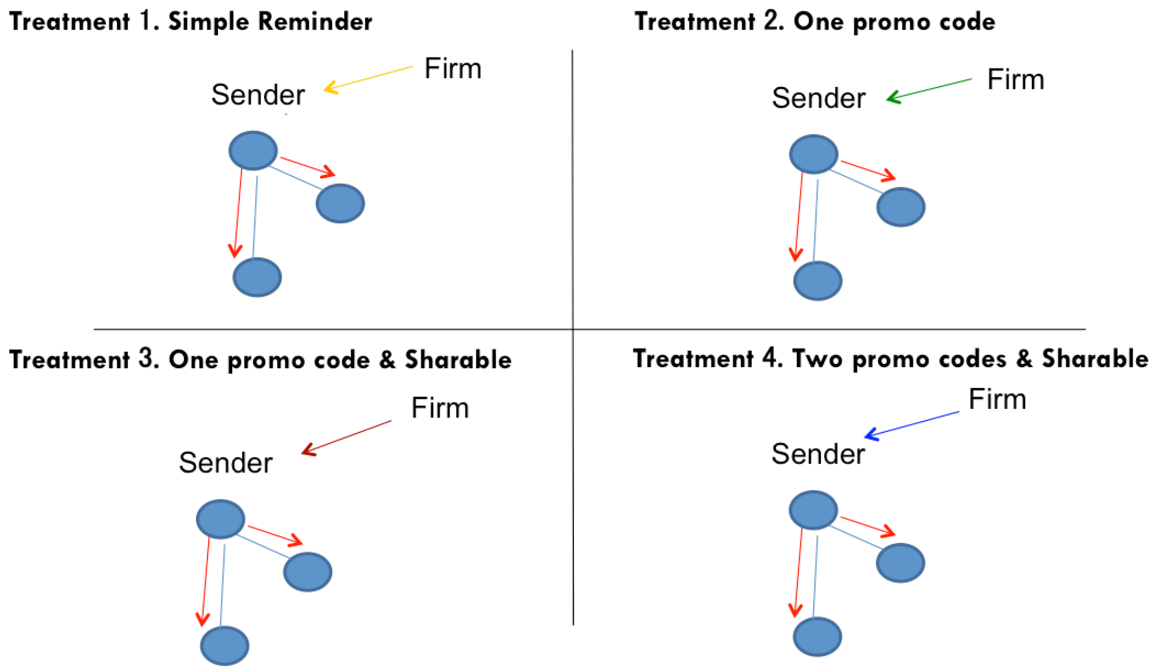


Table 1: Randomization check

Test Group		Sender Characteristics				Deal Characteristics	
	Sample size	Number of past purchase	Total past spending	Days after creating account	% of share through Facebook	Deal Price	Deal Category
C	4309	0.00	0.00	0.00	0.00%	0.00	A list of dummies for every major deal category
T1	4045	-0.12	-6.01	6.08	-1.32%	4.14	
T2	4050	0.14	-0.16	-14.09	0.96%	-1.51	
T3	4007	-0.16	1.86	4.19	-1.36%	-2.29	
T4	4069	0.17	0.52	-0.09	1.25%	3.52	
p value for joint test (C=T1=T2=T3=T4=T5)		0.82	0.99	0.44	0.33	0.34	No significant difference for all deal categories

* To respect NDA, the figures provided are demeaned values obtained by subtracting the mean value of treatment groups from that of control group. Demeaning preserves the difference in mean value between test groups as well as the t-test (i.e. randomization check). Pairwise t-test is available upon request.

Table 2: Self-regarding preference
Main Effect of each treatment on sender's purchase decision

	Sender's Purchase		**Sender's Referral**	
Dependent Variables	Percentage lift in sender's purchase	p-value	Percentage lift in sender's referral	p-value
Effect of Reminder on Sender's Purchase or Referrals (T1-C)/C	14.1%	0.198	7.8%	0.598
Effect of one non-shareable code on Sender's Purchase or Referrals: (T2-C)/C	64.5%	0.000	18.3%	0.286
Effect of one shareable code on Sender's Purchase or Referrals: (T3-C)/C	31.6%	0.002	67.4%	0.005
Effect of two codes on Sender's Purchase or Referrals: (T4-C)/C	27.8%	0.007	29.5%	0.125

Table 3: Other-regarding preference
Main Effect of each treatment on sender's referral behavior

	Total Referrals		**Sender only makes referral (without purchase)**		**Sender makes both referral and purchase**	
Dependent Variables	Percentage lift in average number of referrals from each sender	p-value	Percentage lift in average number of referral from each sender	p-value	Percentage lift in average number of referral from each sender	p-value
Effect of Reminder on Sender's referral (T1-C)/C	7.8%	0.598	9.60%	0.809	-4.7%	0.840
Effect of one non-shareable code on Sender's Referral: (T2-C)/C	18.3%	0.286	17.4%	0.481	20.5%	0.388
Effect of one shareable code on Sender's Referrals: (T3-C)/C	67.4%	0.005	92.5%	0.013	26.2%	0.283
Effect of two codes on Sender's Referrals: (T4-C)/C	29.5%	0.125	11.3%	0.799	47.1%	0.116

Table 4: Group-regarding preference
Main Effect of each treatment on the Co-Purchase decision with friends (sender makes both purchase and referrals)

	All products		**Social product**		**Standalone product**	
Dependent Variables	Percentage lift in the number of senders who makes both purchase and referrals	p-value	Percentage lift in the number of senders who makes both purchase and referrals	p-value	Percentage lift in the number of senders who makes both purchase and referrals	p-value
Effect of Reminder on Co-Purchase (T1-C)/C	-4.7%	0.840	-25.7%	0.542	3.4%	0.899
Effect of one non-shareable code on Co-Purchase: (T2-C)/C	20.5%	0.388	42.7%	0.360	12.3%	0.642
Effect of one shareable code on Co-Purchase: (T3-C)/C	26.2%	0.283	45.1%	0.347	19.4%	0.487
Effect of two codes on Co-Purchase: (T4-C)/C	47.1%	0.116	103.2%	0.051	14.2%	0.595

Table 5: Heterogeneity in treatment effect
Based on the sender's and the recipient's revealed preference on the shared deal

Moderator	**Sender's Preference on the shared deal**		**Recipient's Preference on the shared deal**	
Dependent Variables	**Sender's Purchase**	**Sender's Referral**	**Sender's Purchase**	**Sender's Referral**
Effect of one non-shareable code on Sender's Purchase: (T2-C)/C	0.002	-0.043**	-0.025	0.011
Effect of one shareable code on Sender's Purchase: (T3-C)/C	0.026*	-0.032*	0.002	0.036*
Sample size	20,375	20,375	16,481	16,481

Chapter 4:
Essay 3 -- Motivating Group Donation: Evidence from a Large Field Experiment

4.1. Introduction

Information technology has greatly reduced the communication and coordination cost among individuals. As a result, individuals are connected online and offline, ready to influence each other's behavior on an unprecedented scale. In light of this trend, organizations have increasingly used social interventions (Godes et al. 2005, Hill et al. 2006, Valente 2012), but academic research is lagged behind. More specifically, a large stream of literature has studied online information sharing (Aral and Walker 2011, 2012, Bapna and Umyarov 2014, Ma et al. 2014, Susarla et al. 2012), while much less is known about how firms use digital interventions to improve offline social interaction. As Aral (2015) points out, "…there remains a danger in relying too heavily on digital substrates to explore human behavior. Not only are digital samples biased toward those who are more active online, potentially missing large swaths of society, but limiting inquiry to digital behaviors constrains the theoretical reach of experimental work." Hence Aral (2015) calls for networked experiments to link online treatment with offline response.

My study is one attempt to answer this call. Specifically, I use mobile messaging to leverage recipients' social ties for an important offline behavior – blood donation. Blood shortage is prevalent worldwide, partly due to the low level of voluntary donation, especially among developing countries (WHO 2015). While individual incentives are important[9], recent literature finds that donors behave differently when surrounded by

[9] On economic rewards, see Lacetera, Macis and Slonim 2012, 2013, 2014, Iajya et al. 2013, Goette and Stutzer 2008. On mechanism design, see Kessler and Roth 2012, 2014. On behavioral interventions, see

other donors or watched by third-party observers (Goes et al. 2014, Toubia et al. 2013, Jabr et al. 2013, Ozbay and Ozbay 2014, Ariely et.al. 2009). Such a group effect usually leads to more donations, although its effectiveness depends on group size (Zhang and Zhu 2011), group composition (Chen and Li 2009), and information structure (Chen et al. 2010). In light of this literature, my study offers a new approach to address the global challenge of blood shortage.

Up till now, most studies on group effects employ a researcher-controlled environment that defines group *exogenously*. In reality donor groups are often formed endogenously even before the charitable event organizer greets any potential donor. Therefore, important questions are left unanswered such as: How can we use mobile interventions to encourage potential donors to form a group? Why do people donate or not donate as a group? What kinds of individuals are more prone to the digital interventions in offline social interactions? In this paper, I examine how to take advantage of endogenous group formation to increase donation in a real world setting.

There are multiple reasons why leveraging offline group formation can be more beneficial to society than addressing each donor separately. First, donating in front of a friend may generate extra value to the donor in terms of a more positive social image or warm glow. Second, to the extent that friends are alike, the friend of an active donor is likely a prospective donor. Third, coming to the charitable event together may generate a shared experience valuable to both the donor and her friend. This will in turn enhance the likelihood of the two coming as a group. Fourth, if we can identify what types of donors

Andreoni and Rao 2011. On social pressure and social image, see DellaVigna, List and Malmendier 2012, Kessler 2013, Ariely, Bracha and Maier 2009, Karlan and McConnell 2014, Andreoni and Bernheim 2009.

are more likely to enjoy group donation, reaching out to them can have a long run ripple effect that further spread the benefits of group donation.

If it is so desirable to donate as a group, why don't all donors already donate in a group? One explanation is coordination failure: a donor may need to reach out to her friend and educate him/her about the charitable event, and to coordinate schedule and transportation. The other explanation reflects more fundamental issues such as negative peer pressure (Calvó-Armengol and Jackson 2010): the donor may be reluctant to ask a friend to donate together if doing so amounts to asking for a favor or imposing social pressure on the friend. Whether the lack of group donation is due to coordination failure or negative peer pressure, I argue that encouraging group donation has a potential to improve Pareto efficiency. For example, suppose group donation can generate an extra value of $1,000 to the charity (as compared to solo donation), but it does not occur because the private benefit of group donation is only $500 to the donor and her friend, while the coordination cost and the negative social pressure of asking or being asked sum up to $600. In this case, the charity can offer a $200 reward for group donation, which allows the donor and her friend to receive a net benefit of $100 via group donation and the charity to realize a net benefit of $800.

To study ways to motivate group donation, I collaborated with a Chinese blood bank and conducted a large field experiment in December 2014. I randomly assigned 80,000 potential donors into seven test groups. The first one is a control group with 14,000 subjects. For the remaining six groups (with 11,000 subjects in each), I sent out a mobile message and varied its content across groups. The message content explored two tools to overcome the hurdle of group donation. One is behavioral intervention: some treatments do not mention group donation at all, while the others explicitly request a potential donor to donate together with friend(s). The second tool is providing economic reward for solo or group donation. My experimental design incorporates six combinations of these two tools (Table 1).

In particular, message 1 only reminded subjects to donate, message 2 added an explicit reward for donation (a supermarket voucher that is worth 30-50 RMB, equivalent to 6-8.3 US dollars). The average daily wage in this city in 2014 was about 100 RMB, so the reward amount is non-trivial. Neither message 1 nor 2 mentions group donation. In message 3, I reminded the subject to donate with friend(s), but did not mention the economic reward for donation; message 4 included both a reminder for donating with friend(s) and the economic reward. Note that in both message 2 and message 4, the reward is presented as reward per donor, without any condition on whether the donor comes alone or with friend(s). Message 5 is similar to message 4, except that I made the reward conditional on donating with friends ("…if you and your friend(s) donate together, each one of you will get a reward of…"). Message 6 is similar to message 4, but highlighted additional gifts available for all donors that come in group ("… you will get a reward of … upon donation. If you and your friend(s) donate together, each one of you will get an additional gift."). Table 1 summarizes the behavioral intervention and economic rewards in each treatment group, together with their corresponding parameters in my model (introduced in Section 3). For every donor who showed up during the experiment period, I also conducted a detailed survey that includes questions on their perception of social image and donating in a group.

My experiment generates three main findings. First, a subject's donation decision – none, solo, or group donation – depends on both the reminder to donate and the economic reward for donation. Compared with the control group, receiving a message that encourages donation (message 1) has a positive effect on the overall donation rate, but receiving a message that encourages donation with a friend (message 3) has no significant effect. This suggests that simply mentioning group donation does not work: while the message reminds donors of the pleasure of donating with a friend, it also increases the perceived costs associated with getting a friend and convincing him to donate, which might even backfire and hurt donation rate. When I added economic reward to the mobile message (messages 2,4,5,6), the effect on donation rate is always positive and significant, but the effect is of the largest magnitude when the reward is conditional on donating with friends (message 5), especially for those who have donated within the past 9 months. Not only does the conditional reward lead to a higher donation rate from message recipients, but these recipients are also more likely to bring friends who also donate at the same time.

The second main finding is that different messages tend to attract different types of donors. Thanks to my randomization design, all seven control and treatment groups are similar in observable demographics. However, the donors who respond to message 5 (with economic reward conditional on group donation) are more likely to be married, to be older than 35, to have local resident permit (hukou) in the city, to have donated more recently, and to have donated more times before the experiment than donors responding to other messages. It is interesting to note that this group of people tends to be less active in online social platforms compared to those who are younger and single (Pew Research

Center 2014). However, my finding suggests that they are more prone to my digital interventions, possibly because of stronger social ties in local area. Survey results confirm that donors responding to message 5 are more willing to share the donation experience with family and friends, to bring a friend next time, and to believe that encouragement from friends are important to motivate donation.

Thirdly, across all treatments, message recipients donate a greater amount of blood if their friends are present, regardless of whether their friends donate or not. This confirms the group effect demonstrated in the literature, and suggests that a friend's presence provides another margin to increase donation even if the friend does not donate.

I further fit my experimental data into a structural model, in order to shed light on the optimal design of incentive scheme and targeting strategy. I find that rewarding group donors is four times more cost-effective than rewarding individual donors in motivating blood donation, as the bank only needs to reward donors who come in groups and enjoy even more donation amount when people donate in front of friends. The cost that the bank needs to pay to donors is calculated to be 50RMB per unit of blood (400ml) under individual reward and 10.2RMB under group reward, both of which are arguably well below the social value of having one additional blood unit available. The blood bank can further improve the cost efficiency by targeting a subset of donors that tend to respond more positively to group reward, namely female donors who are local, married, highly educated and have donated recently.

Altogether, my experiment suggests that charities can leverage endogenous group formation to stimulate voluntary donation, but only if it is bundled with appropriate economic incentives. With group reward conditional on donating together with friends, charities can attract a special group of donors that are more pro-social and more likely to share donation experience and recruit donors through their social networks. In the rest of the paper, I first present a simple model in Section 2, and then describe the field experiment design in Section 3. Reduced-form results are reported in Section 4, followed by structural estimation and counterfactual simulations in Section 5. A brief discussion is offered in Section 6.

4.2. Model

Consider a potential donor i who faces the decisions of not donating (d=0), donating alone (d=1, g=0), and donating with a friend (d=1, g=1)[10]. Let me normalize the utility from non-donation as zero ($U_i(d = 0) = 0$). If i donates Y_d amount of blood, her utility consists of a fixed component and a variable component. The fixed component captures the economic and non-economic rewards of donating the minimum amount (200ml) minus the related time, transportation, health and psychological cost ($\alpha^d - C^d$). Additional economic reward for the donor is reflected in M^{sr}. If i brings a friend, donating 200ml also generates positive social image or warm glow in front of the friend (α^g), but it also entails a cost of asking and coordinating with the friend (C^g). This includes the cost of finding such a friend, educating him/her, persuading him/her to donate together, and in the future returning the favor if the friend consents to donation due to the social pressure from i. Here I abstract from the detailed search process that i may engage in to find friend and form a group. It is worth noting that the cost of persuading a friend to donate together may depend on the reward that the blood bank

[10] For simplicity I assume the friend will donate blood. In Section 5, I introduce another variable f to differentiate the two situations: the friend donates (g =1, f=0), and the friend does not donate (g=1, f =1).

offers to the donating friend. The bank can also offer group reward to i for bringing in a donating friend, which is included in the benefit of bringing a donating friend (M^{gr}) [11].

In the fixed component of donation utility, I assume there is one cognitive cost of remembering to donate at all and another cognitive cost of remembering to bring a friend. Receiving the reminder message to donate (DMSG=1) or a reminder to bring a friend (GMSG=1) will therefore increase the utility of donation (Karlan et.al. 2010). In addition, if a subject receives GMSG from the bank but donates alone, this incurs a cost associated with the social pressure, because she may feel guilty for not fulfilling the request. I denote this social pressure from the bank as C^{sp}, which by definition only occurs when d=1 and g=0.

In combination, the utility from the decisions {d, g} can be expressed as:

$$U_i(d=0)=0$$

$$U_i(g|d=1)=\alpha^d - C^d + \beta^{DMSG}\cdot DMSG - C^{sp}\cdot GMSG\cdot(1-g) + \beta^{sr}\cdot M^{sr}$$

$$+(\alpha^g - (C^g - \beta^{fr}\cdot M^{fr}) + \beta^{GMSG}\cdot GMSG + \beta^{gr}\cdot M^{gr})\cdot g + \varepsilon^{idg}$$

$$Likelihood(d,g) = prob\big(U_i(d,g) > U_i(d',g')\big)$$

$$\forall\,\{d',g'\} = \big\{\{0,0\},\{1,0\},\{1,1\}\big\}$$

Individual i chooses {d, g} to maximize her utility. As described in Section 1, my field experiment varies DMSG, GMSG, M^{sr}, M^{fr} and M^{gr}.

This model captures several incentives for group donation. First, if bringing a friend yields net positive benefits to individual i, it may convert her from no donation or solo donation to group donation. Second, from the bank's perspective, if the incentives for group donation through α^g and M^{gr} are not high enough, the request for group donation

[11] My model in section 5 has a more general setup where reward can be separately given to each group member.

may backfire because it introduces social pressure C^{sp} on the donor. Such social pressure, if substantial, may persuade a potential solo donor into no donation at all. Third, in the presence of a friend, one may donate a higher amount, and the extra benefits of donating more in front of a friend may affect the donor's decision of whether and how to donate in the first stage.

The first and second points can be illustrated in Figures 1-4. For the purpose of illustration, I ignore the option of bringing a non-donating friend and restrict donation amount to a fixed level of 200ml – more variations are included in the full model and empirical analysis. In Figure 1, I define the vertical axis $\mathcal{H}$ as the benefit of donation that individual i expects to get regardless of whether she brings a friend or not. Following previous notation, $\mathcal{H} = \alpha^{d} - C^{d} + \beta^{DMSG} \cdot DMSG + \beta^{sr} \cdot M^{sr}$. The horizontal axis $\mathcal{L}$ is defined as the extra benefit i can get from group donation if she brings a friend. Mathematically, $\mathcal{L} = (\alpha^{g} - (C^{g} - \beta^{fr} \cdot M^{fr}) + \beta^{GMSG} \cdot GMSG + \beta^{gr} \cdot M^{gr})$. Figure 1 describes a benchmark case where $DMSG = GMSG = M^{sr} = M^{fr} = M^{gr} = 0$ (which corresponds to my control group). In this case, Figure 1 shows that (1) i will not donate in the yellow area because $\mathcal{H} < 0, \mathcal{H} + \mathcal{L} < 0$; (2) i will donate alone in the green area where $\mathcal{H} > 0$ & $\mathcal{L} < 0$, and (3) i will donate with a friend in the blue area where $\mathcal{L} > 0$ & $\mathcal{H} + \mathcal{L} > 0$.

Figure 2 increases the return to solo donation from $\mathcal{H}$ to $\mathcal{H} + \Delta\mathcal{H}$. This can be achieved by offering more economic reward to solo donation (i.e. increase M^{sr}) or by sending a reminder message to the donor and reducing her cost of remembering to donate (i.e. change $DMSG$ from zero to one). Comparing with Figure 1, an increase in $\mathcal{H}$ leads some non-donating people to donate alone (the black-line shaded area that turns green from yellow), and some non-donating subjects to donate with a friend (the white-line shaded area that turns blue from yellow).

Similarly, compared to Figure 1, Figure 3 increases the extra return to group donation (as compared to solo donation) from $\mathcal{L}$ to $\mathcal{L} + \Delta L$. This can be achieved by rewarding i for donating with a friend (i.e. increasing M^{gr}), providing economic reward $M^{fr}$to the donating friend and therefore reducing the cost of i persuading a friend, or sending a reminder message for i to bring a friend (i.e. changing $GMSG$ from zero to one but assuming $C^{sp} = 0$).

Figure 2 and Figure 3 show some interesting contrasts. Compared to Figure 1, both of them convert some non-donors into group donors (the lower shaded area with white lines). This is because for some people group donation is more desirable than solo donation ($\mathcal{L} > 0$), but the total benefits are not big enough to overcome the associated cost ($\mathcal{H} + L < 0$). The introduction of $\Delta\mathcal{H}$ or $\Delta\mathcal{L}$ helps to boost them into group donation. In addition to this common effect, Figure 2 brings in another group of donors who do not donate in Figure 1 but become solo donors in Figure 2 (the shaded area with dark lines). These new donors are primarily those who expect negative benefit from group donation ($\mathcal{L} < 0$) but are almost ready to donate solo ($\mathcal{H} < 0$ & $\mathcal{H} + \Delta\mathcal{H} > 0$). In comparison, Figure 3 brings in another group of donors who would have donated by themselves in Figure 1 but now donate in group in Figure 3 (the upper shaded area with white lines). These always donors need a nudge to overcome some small net cost of group donation ($\mathcal{L} < 0$ & $\mathcal{L} + \Delta\mathcal{L} > 0$). In summary, the difference between Figure 2 and Figure 3 suggests that all donors responding to the increased reward for group donation will come in group, while some donors responding to the increased reward for solo donation will come solo.

Figure 4 allows for social pressure for not bringing a friend upon the bank's message for group donation (C_{sp}>0). In this case, receiving a group message but donating alone needs to overcome the social pressure C^{sp}. Therefore, compared to Figure 1, the yellow no-donation area expands ($\mathcal{H} - C^{sp} < 0, \mathcal{H} + \mathcal{L} < 0$), the green donation-alone area shrinks ($\mathcal{H} > C^{sp} \& \mathcal{L} < -C^{sp}$), and the blue group-donation area expands ($\mathcal{H} + \mathcal{L} > 0 \& \mathcal{L} > -C^{sp}$). In other words, when the bank's request for group donation imposes a social pressure, the pressure may lead to more group donation (the white-line shaded area) but less solo donation (the dark-line shaded area).

In summary, the model has a few testable implications: 1) DMSG will lead to more solo donation and more group donation, GMSG will lead to less solo donation but more group donation; 2) An increase in the reward for solo donation will lead to more solo donation and more group donation; 3) An increase in the reward for group donation will lead to more group donation and less solo donation, but the total donation should always increase; 4) Reward for solo donation and reward for group donation are driving different types of donors. Donors who are motivated by individual reward are likely to have relatively high utility for solo donation; donors who are motivated by group reward are likely to have relatively high utility for group donation.

4.3. Background and Experiment Design

I collaborated with a centralized blood bank in a provincial capital city in China with a population of over 8 million. The blood bank is responsible for supplying blood to 18 hospitals in the city and is encouraged to be self-sufficient in blood supply. In the past ten years, the blood bank has recruited more than 400,000 whole blood donors, who have contributed more than 500,000 donation episodes. The donations are collected using 17 bloodmobiles spread across the city and by special drives at specific universities, companies and government agencies. My experiment focuses on individual donations collected by bloodmobiles.

The experiment was run in the 15-day period from late December 2014 to early January 2015. I started by choosing participants from past donors of the blood bank based on three criteria: first, the blood donated by the particular donor must pass a battery of blood test, which is important because the bank aims to increase supply of qualified blood; second, the donor has not donated in the last six months, as a 1998 nationwide law disallows any donor from donating whole blood twice within six months; third, the donor has made at least one donation in the past 25 months. Because donors that only donated long time ago may have moved out of the city, the last criterion is used to better capture donors that are still living in the city.

A sample of 80,000 participants who were registered as past donors was randomly assigned into seven test groups. The first one is the control group with 14,000 subjects who received no message from the blood bank. The remaining six groups (with 11,000 subjects in each) received different mobile messages as described in Section 1.

Once the participants decided to donate and visited the bloodmobile (either alone or in group), they first filled out a standard questionnaire on demographics and medical conditions, designed by the blood bank to evaluate their eligibility of making donation. The donors then underwent a blood screening test. While waiting for the test results, they were asked to fill out an additional survey designed by the researchers (approximately 10 minutes). The nurse then collected the survey and informed donors of the standard gifts and special rewards they would receive based on the donation amount. The donors would then decide how much to donate and make the donation.

In particular, donors who choose to donate 200ml would receive standard gifts (e.g. souvenir such as cup or t-shirt). Donors who donate 300ml of blood were eligible for a 30RMB supermarket voucher (around $5), and those donating 400 ml were eligible for a 50RMB supermarket voucher. In addition, group donors received an additional gift: a fruit cutting gear (worth about 10RMB) for each of them. These rewards were dispensed to all donors, regardless of whether they were in my experiment or what text message they have received from the bank. In other words, participants in different treatments only differ in the message from the bank, not the actual gifts upon donation. Because all my messages with economic reward mentioned the reward as "30-50 RMB in supermarket voucher" and did not link the exact reward to donation amount, I believe most participants in my experiment did not know the correlation between reward and donation amount until they came near a bloodmobile. This implies that the differential reward by donation amount should not affect the decision of whether to donate (solo or with a friend) but it will affect the donation amount after one has approached the bloodmobile.

After each donation, the nurse completed two tasks. First, the nurse marked the donor ID on each survey, which would help me link the survey to the donor; second, if the donors donated in a group or a donor brought non-donor friends, the nurse recorded donor ID of each donor in the group, as well as the number of non-donor friends with them. All nurses on the bloodmobile went through a centralized training session before the campaign and are instructed to strictly follow the same procedures in administrating the donation.

For every donor who participated during the experiment period, I also conducted a detailed survey which is designed to help me identify unobserved constructs such as a donor's social environment (e.g. whether friends and family donated before, coordination cost), image motivation (willingness to share donation experience, and the channel to share) and relationship with other donors in group. Finally, I augment the data from the field experiment with rich archival data, including demographics (age, gender, education, occupation, marriage status, resident status, and health indicators) and donation history (across 10 years) for the 80,000 subjects in my experiment.

4.4. Reduced-form Evidence

This section reports the reduced-form effect of treatments on the share of donors who choose to donate (d=1), the amount of donation by donors, and the total amount of donation by donors and their friends. From now on, I use "donors" to refer to the donors that are my experiment subjects. Friends of donors who donated are referred to as "donating friends".

Before presenting the main results, I first check the validity of randomization. As shown in Table 2, there is no detectable variation across the groups in terms of gender, age, marriage status, residency, and the number of past donations. The t-tests on these variables across groups are insignificant at conventional level. The well-balanced sample indicates that my randomization is at work.

Table 3 summarizes key outcomes across treatment groups. Panel A focuses on subjects' own decision to donate (d). On average, the donation rate in my sample during the campaign period is about 1%, which is consistent with previous studies on blood donation (e.g. Lacetera et.al. 2012, 2014). Comparing T1 to T0 shows that there is a sizable reminder effect. While the donation rate is 0.71% in T0, that number jumped to 0.98% in T1. More interestingly, groups with economic rewards (T2, T4, T5, and T6) show additional gain in boosting donation rate beyond the reminder effect, with donation rates all greater that 1%. This suggests that economic reward have a noticeable effect in motivating potential donors. The most striking increase is T5, with a relative increase of more than 60% over the control group (from 0.71% to 1.17%).

Further examination reveals that donor demographics differ by treatment, as presented in the right columns of Table 3 Panel A. Donors from the group reward treatment (T5) are more likely to be married, local, older, more recent in the last donation, and have more donations in the past. In contrast, subjects who donate under individual reward treatment (T2) are more likely to be unmarried, non-local, younger, last donated long time ago, and have fewer past donations. In summary, this panel shows evidence that both individual reward and group reward are effective, but they may motivate different types of donors. This is consistent with my model.

Table 3 Panel B focuses on the subjects' decision to donate in group, conditional on self donation (d=1). There are two outcomes related to a donor's group donation decision: whether to donate with a friend, and her own amount of donation. Both outcomes vary across treatments. Since the friend might or might not donate, I focus on the percentage of donors who bring donating friends, as my research goal is to motivate more donations.

One might think that reminding a donor to bring a friend (T3) will lead to more donating friends. As shown in Column 7 (second to last column), this is not true. The behavior intervention alone (T3) is not effective in motivating friends at all. However, once the group reward is added to the treatment, there is a large increase in donating friends (1.05% in T3 vs. 10.85% in T5). In contrast, individual reward does not lead more group donations when compared to the control group. As to the amount of donation, I find that donors are likely to donate more blood when friends are present (Column 8), even when the friends do not donate (Column 6). This is consistent with the image motivation effect identified in the literature (Ariely et al. 2009)

While the summary statistics provide suggestive evidence on the impact of treatments, I formally test such impact using regressions. Table 4 provides reduced form estimates of the treatment effects on various outcomes. Panel A presents results of an OLS regression on the full sample (80,000 donors)[12]. First, results in Columns 1 and 2 suggest that the effects of reminder message (T1) and individual reward (T2) on a donor's donation decision (d) are both positive and significant. Then adding request to bring friends on top of reminder message (T3) seems to dampen donation (though the difference between T1 and T3 is not statistically significant). This may be driven by the fact that the request to bring friends imposes social pressure on the subject and therefore discourages those donors who cannot meet the request. Interestingly, once the individual reward is coupled with the friend reminder (T4), the negative social pressure is overcome and there is a large increase in donation rate. The group reward (T5) works even better in promoting donation. Comparing T4 to T3, as well as T5 to T3, suggest that the economic reward has

[12] I report estimates based on linear OLS in Table 4 for easy interpretation of the results. The findings are robust to alternative estimation methods such as the logit regression.

a significant impact on donation. In contrast, adding an additional group gift on individual reward (T6) does not lead to a significant lift in donation rate, which suggests that the incentive might have saturated.

Columns 3-4 of Table 4 Panel A reports the effect of treatments on an alternative outcome variable: the subject's amount of blood donation. The value is set to 0 if the subject does not come to donate. The result is similar to findings in Columns 1-2, suggesting a substantial increase in T1, T2, T4, and especially T5, but not T3.

I also examine the effect of treatments on the volume of friend donation in Columns 5-6 of Table 4 Panel A. The dependent variable is created by aggregating the donation amount of all donating friend(s) in a donor's group. Consistent with the above summary statistics, only the group reward is effective in increasing the amount of donation from friends. The magnitude of increase is non-trivial as compared to solo donation (0.50ml increase in donation from friends vs. 1.88ml increase in donation from self).

Finally, I construct the volume of total donation by adding the donation amount from the subject herself and the donation amount from her friends (if any). In this way, the dependent variable can capture the additional blood supply due to group donation, which is of central interest to the blood bank. As shown in Columns 7-8, the effect of economic reward on the total blood supply is significant. Compared to the average donation amount in the control group (2.49ml per subject), adding group reward leads to an increase of 2.47ml, almost 100 percent more in supply, which is bigger than the effect of individual reward (1.59ml) at the 10% significance level after I control for subject age, gender and weight (Column 8).

Panel B of Table 4 evaluates the treatment effects on the same set of outcomes, but conditional on a subject's donation (d=1). While the sample size is much smaller, Table 4 provides statistically significant evidence that group reward is effective in motivating subjects to donate with friends, which leads to great blood supply through extensive margin.

Panel C of Table 4 divides the experimental sample according to whether a subject's last donation was no more than 9 months ago, 10-14 months ago, or more than 14 months ago. Consistent with Lacetera et al. (2014), I find that economic rewards are more effective on the subjects that donated more recently last time. Interestingly, if I focus on the subjects that donated no more than 9 months ago, group reward (T5) motivates significantly more blood donations than individual reward (T2). This difference is driven by both a higher likelihood of solo donation and a higher likelihood of bringing a donating friend. One explanation is that it is easier to share a donation experience with friends if it happened not long time ago. It is also possible that those who donated more recently last time are more pro-social.

Table 5 switches perspective and focuses on the intensive margin. I regress the donor's donation amount on whether she is donating with (donating or non-donating) friends. The positive and significant coefficient on the binary indicator suggests that donors who donate in group are also donating more blood, *regardless of* the treatments they are exposed. This finding is well aligned with the previous literature and provides another key rationale for the higher efficacy of group donation. In this way, I close the loop and confirm benefits on both extensive margin and intensive margin yielded by the group reward.

Analyses of the heterogeneous treatment effects and the survey data are presented in Tables 6 and 7. In particular, Table 6 looks at two outcomes – the dummy of self donation and the total amount of blood donated by self and friends. Each column includes the interaction of one demographic variable and all the treatment dummies.[13] These regressions suggest that group reward encourages more donation from subjects that are married, local, older, and with more recent donation and more past donations, probably because these people are likely to have a lower cost of bringing friends. While these people are generally less active in online social setting, my study suggests that with the right incentive design, digital interventions can be used to leverage their offline social connections. In this way, organizations may take advantage of the relative strength of this population in social interactions. Using survey data, Table 7 shows that donors that are motivated by group reward are more likely to hear about friends donating in the past, more willing to share the donation experience, and more willing to bring friends to donate together in the future.

4.5. Structural Estimation and Counterfactuals

So far, the reduced-form estimates suggest that economic reward matters and group reward can be effective in motivating donation from a specific type of donors. In this section, I estimate a structural model, which is closely tied to my experiment design, and brings several advantages compared to the reduced-form estimates. First, by leveraging the variation of messages in my experiment design, the structural model can separate and quantify the effect of each element in my treatments. Second, the structural model allows

[13] I do not put all demographics in one regression because many of them are highly correlated.

me to simulate different combinations of behavior intervention and economic reward, and the counterfactual simulations provide deeper insights for optimizing the incentive design. Finally, by allowing certain parameters to vary by demographic variables of donors, the structural model also enables me to assess donor heterogeneity, which generates insights on targeting different types of donors with the most effective mobile interventions.

4.5.1 Structural Model

In the first stage, the subject makes a joint decision {d, g} about whether to donate and whether to donate with friend(s) in a group, based on her own primitives as well as the exogenous treatment. Her own primitive includes the utility derived from the donation α^d, cost of making the donation C^d, as well as the utility of donating in a group α^g, and the cost of bringing friend(s) to form a group C^g. The exogenous variations in my field experiment include sending a reminder message for donation sending a reminder message for donation (DMSG), requesting for group donation in the reminder message (GMSG), offering reward for the message recipient's donation herself (M^{sr}, referred to as self reward), offering reward for the message recipient if she donates with a friend in a group (M^{gr}, referred to as group reward), and offering the economic reward for the donating friend of the message recipient (M^{fr}, referred to as friend reward). It is worth noting that the three types of rewards work in different ways. M^{sr} directly compensates the donation cost of the focal donor; M^{gr} compensates the sum of donation cost and cost of bringing friends; in contrast; M^{fr} indirectly influences the focal donor by reducing his/her cost of persuading friends to donate.

In the second stage, the subjects who come to the bloodmobile are informed of the standard gifts and special rewards they will receive based on donation amount upon their choice (Y_d). Donating 300ml or 400ml (instead of 200ml) would earn the donor an additional economic reward, which I denote as M_{300} or M_{400}; but at the same time donating more blood in a single episode incurs a higher cost, which I denote as C_{300} or C_{400}. In addition, donating 300ml or 400ml in front of a non-donating friend (f=1) or donating friend (g=1) may allow the donor to gain additional utility (either through positive image or altruism), which I denote as S_{300f}/S_{400f} or S_{300g}/S_{400g}.

Since my mobile messages is designed such that *no information* is given about how reward may differ by donation amount, a donor's first-stage decision on {d,g} is independent of the second stage decision of donation amount. This allows me to model the two stages separately. Another simplification is that I do not consider the possibility of bringing a non-donating friend separately from coming alone in the first stage. This is because all the group reward offered in my mobile message treatment is conditional on bringing a donating friend. Because the two stages are modeled separately, I allow donation amount to be dependent on whether a non-donating friend is present, in order to capture the potential effect of being observed by a friend.

Assuming the impact of all rewards is linear, I can write the latent utility function for the donor's decisions in the first stage as:

First Stage:

$$U_i(d=0)=0$$

$$U_i(g|d=1)=\alpha^d-\ C^d+\beta^{DMSG}\cdot DMSG-C^{sp}\cdot GMSG\cdot(1-g)+\ \beta^{sr}\cdot M^{sr}$$

$$+(\alpha^{g} - (C^{g} - \beta^{fr} \cdot M^{fr}) + \beta^{GMSG} \cdot GMSG + \beta^{gr} \cdot M^{gr}) \cdot g$$

$$+ \gamma^{10} \cdot (1-g) \cdot X_i + \gamma^{11} \cdot g \cdot X_i + \varepsilon^{idg}$$

$$Likelihood(d,g) = prob\big(U_i(d,g) > U_i(d',g')\big)$$

$$\forall \{d' \ , g'\} = \big\{\{0,0\},\{1,0\},\{1,1\}\big\}$$

Second Stage:

$$V_i(Y_d|d=1,g,f) = \big(M_{300} - C_{300} + \beta_{300f} \cdot f + \beta_{300g} \cdot g\big) \cdot (\, Y_d = 300)$$

$$+\big(M_{400} - C_{400} + S_{400f} \cdot f + S_{400g} \cdot g\big) \cdot (Y_d = 400)$$

$$+ \theta^{10} \cdot (Y_d = 300) \cdot X_i + \theta^{11} \cdot (Y_d = 400) \cdot X_i + \varepsilon_{ifgY}$$

$$Likelihood(Y_d) = prob\big(V_i(Y_d) > V_i(Y_d')\big)$$

$$\forall \ \{Y_d|d=1\} = \{200,300,400\}$$

For each stage, I estimate a conditional logit model using maximum likelihood. The vector of parameters that I estimate for the first-stage decision are: i) the net utility derived from donation minus donation cost: α^{d}-C^{d}; ii) the decrease in mental cost when receiving the reminder message for donation: β^{DMSG}; iii) the increased donation cost of social pressure if request to bring friend cannot be met: C^{sp}; iv) the decreased mental cost of bringing a friend thanks to the reminder message: β^{GMSG}; v) the increased utility derived from receiving economic rewards: β^{sr} and β^{gr}; vi) the utility derived from donating in front of a friend (like warm glow) α^{g}, and the cost of persuading a friend to join as a group. Specifically, C^{g} is the default cost of persuasion if no incentive is offered to the friend, and β^{fr} represents the cost savings if an economic reward is offered to a friend, in forms of either direct economic reward M^{fr}, or group incentive M^{gr}, or both. β^{gr} represents the increased benefits for the message recipient to bring a donating friend if the group reward M^{gr} increases by one unit; vi) a vector of coefficients on individual characteristics (including gender, age, weight, local resident or not, years of education) for each outcome: γ^{10}, γ^{11}.

The vector of parameters I estimate for the decision in the second stage are: i) the utility derived from donating more than 200 ml net of the additional donation cost: $M_{300} - C_{300}, M_{400} - C_{400}$; ii) the increased utility from donating more than 200ml in front a non-donating friend: S_{300f}, S_{400f}; iii) the increased utility from donating more than 200ml in front a donating friend: S_{300g}, S_{400g}; and iv) a vector of coefficients on individual demographics (including gender, age, weight, local resident or not, education years) for each outcome: θ^{10}, θ^{11}. For the above parameters, the main sources of identification are my experimental treatments and individual demographics.

4.5.2 Structural estimates

Table 8 reports the MLE estimates for the first stage decision. The net utility of solo donation (α^d-C^d) is precisely estimated as -5.84. In comparison, the most effective behavior intervention (reminder message) or economic rewards (50 RMB of group reward) only lead to an increase of utility by 0.31 and 1.11, respectively. The highly significant negative cost for solo donation is consistent with the observation that only 1% of subjects come to donate during the campaign. Moreover, the net utility of bringing donating friends is estimated to be -2.81, which represents the additional cost involved in donating with friends. This suggests that many donors may have significant difficulty in getting donating friends.

I now turn to the effect of behavioral intervention and economic rewards in overcoming these costs. The reminder message for solo donation is effective in reducing the mental cost, with an estimated value of 0.31. However, the reminder to bring a friend has little extra impact on either solo donation or group donation. On the other hand, I find that the reward for self-donation contributes relatively little value beyond the reminder message. The estimated utility increase from self reward is about 0.10 for 50 RMB. In contrast, the group reward significantly increases the utility of group donation. The estimated utility increase from a reward for group reward is about 1.11 for 50RMB. I also find friend reward is effective in reducing the cost of bringing a donating friend (about 1 for 50RMB).

Table 9 reports the MLE estimates for the second stage decision on donation amount. I find that the presence of both non-donating friends and donating friends would increase the probability of the donor donating more blood. Interestingly, the effect of non-donating friend on this intensive margin is larger, which is consistent with previous literature documenting a strong impact of observer on donor's behavior (Ozbay and Ozbay 2014). In addition, I also find the economic rewards for donating more blood outweigh the cost of additional blood donation (the estimated value of both "net utility for donating 300ml" and "net utility for donating 400ml" is positive and significant). Such effect is stronger for the choice of donating 400ml as compared to that of 300ml.

Overall, the structural estimates echo my reduced-form findings. Below I take a further look into the distribution of primitives for different demographic groups.

4.5.3 Heterogeneity in the population

Panel B in Table 8 shows a large heterogeneity in the distribution of donation cost for both solo and group donations across demographic subgroups. I focus on four demographic variables in my discussion: marriage status, local residency, gender, and education. As illustrated in Figures 5 and 6, I find marriage and local residency of a subject strongly affect her/his cost of donation, and the demographic variations follow the same pattern for solo and group donations. More specifically, married subjects are likely to enjoy greater cost reduction in solo and group donations (around 0.53 and 0.56 for each cost, respectively). Being local also significantly reduces the cost of solo and group donations, with a magnitude similar to that of age (around 0.50 for each cost). In contrast, gender and education have a significant impact on donation cost but its impact is opposite for solo and group donations. Taking gender as an example, while male subjects are in general more likely to have lower cost for solo donation than females, they on average have a higher cost to bring friends. These findings echo previous studies on the gender difference in altruism (Andreoni and Vesterlund 2001). Similarly, less educated donors have lower cost for solo donation than highly educated donors, but in general have more difficulty identifying and bringing a friend to donate together. Finally, the correlation between gender and education is as low as 0.013, suggesting that the two demographics variables may influence the cost of solo and group donations through separate channels. Interestingly, the heterogeneity in the distribution of donation cost for the intensive margin (i.e. donation amount) is also large. Donors who are female, local, married and less educated are more likely to donate larger amount of blood.

The two types of heterogeneity, namely age and local residence, affect solo and group donations in the same direction. On the other hand, gender and education affect the two donation costs in opposite directions (Figures 5 and 6). These have important implications for blood banks. On one hand, blood banks can target past donors who are male, less educated, married and local to increase the conversion rate in donor recruitment. On the other hand, if blood banks wish to take advantage of group effect and motivate group donation, they should target past donors who are female, highly education, married and local. Overall, my findings suggest that blood banks should carefully align their campaign goal with donor targeting strategy.

4.5.4. Counterfactuals

Equipped with the structural estimates, I perform a series of policy simulations to compare different combinations of behavior intervention and economic rewards, reported in Table 10. Consistent with the previous discussion, I find that a reminder message for donation is the only effective approach in behavioral interventions. In comparison, all three types of economic reward – self, friend and group rewards – are effective in driving total blood supply. However, they increase total donation through different margins. Self reward mainly increases the solo donation rate; Friend reward alone or group reward alone only increase the group donation rate by 0.04 to 0.05 percentage points; however, when the two are combined, group donation increases by 0.13 percentage points. The joint use of friend and group rewards are effective in that group reward motivates the donor to bring friends, while friend rewards helps her to persuade and compensate her friend. Finally, when the three rewards are used together, I see increase in both solo and group donations, but no synergy effect is observed. This finding is consistent with my model that reward for solo donation and reward for group donation tend to motivate two different types of donors in the population.

More interesting is the comparison between the effect of self reward and that of friend plus group rewards. The former has been commonly used by the blood bank, while the later is new and not used until the experiment. I want to highlight two key differences. First, compared with self reward, the joint use of friend and group rewards encourages the group donation rate to increase 0.1 percentage points but leads the solo donation rate to decline 0.06 percentage points. This pattern reflects the nature of group reward: when there is no reward for solo donation but high reward for group donation (for both the donor and her friend), then donors are much more likely to sort into group donation. The absence of self reward shifts solo donors to group donors. This shift is only possible if the inherent cost of group formation is not too high, as compared to the cost of solo donation; otherwise the decline in solo donation would outweigh the increase in group donation.

Second, I wish to emphasize the cost advantage of friend/group reward over self reward. As suggested in the last column in Table 10, the payment per unit of blood supply for friend or group reward is more than four times cost effective than that in self reward. This is because friend/group rewards would only occur if donors donate in a group. Thus in the majority cases where donors donate alone, the blood bank would not pay any reward --- those donors are willing to donate anyway. The saved budget may be used to increase the stakes in friend/group rewards. As shown in Table 10, at the same level of reward (75RMB (1.5unit) for group reward + 75RMB for friend rewards vs. 75RMB for self reward, or 100RMB (or 2 unit) for group reward + 100RMB for friend rewards vs. 100RMB for self reward), the joint use of group and friend rewards would lead to more blood supply at significant lower cost per donor.

Finally, friend and group rewards can be combined with targeting. As reflected in Figures 5 and 6, the blood bank can target group rewards on female donors who are local, married and highly educated, to generate even higher cost-benefit efficiency in increasing blood supply.

4.6. Discussion

How should charities use digital intervention to encourage offline social interactions? My field experiment reveals the complex nature of using mobile messaging to leverage blood donor's social connections, and generates insights on a donor's decision making process. I show that appropriate economic rewards are needed for the donor to overcome the social cost of motivating friends to donate; otherwise the mobile message of soliciting friends can backfire. The counterfactual analyses using simulation provide more precise recommendations for policy application.

This study answers a recent call to link online treatments with offline response (Aral 2015). It expands IS studies on social interactions using experiments (ex. Aral and Walker 2011, Bapna and Umyarov 2014, Zhang and Zhu 2011), by examining how charities take advantage of endogenous group formation to encourage one important offline behavior – blood donation. Specifically, my study suggests that individuals who are traditionally less active in online social interactions may have a lower social cost in the offline setting. Thus, firms and organization can take advantage of such comparative strength and use digital interventions to leverage their offline social connections. Methodologically, my behavioral model is linked tightly to the experiment design, which allows me to structurally estimate the parameters of interest. To my best knowledge, my work is among the first to integrate field experiments with structural modeling in the IS field, and my approach can be applied to examine the effect of other IT interventions.

The study also contributes to the growing literature of voluntary donation (ex. Jabr et al. 2014, Goes et al. 2014, Lacetera et al 2012, 2014; Andreoni and Rao 2011; DellaVigna et al 2012). While various monetary and behavioral interventions have been examined in the literature, they mostly focus on individual donors. Building on the existing studies, I am among the first to extend the scope of the study to examine how to motivate a donor to bring her friends to donate together. While this paper focuses on blood donation, I conjecture that my results are likely to be applicable to other pro-social activities, such as environmental protection, social work to help children in poverty or seniors with chronic illness, and other community services. My results should especially benefit those organizations that are constrained by financial resources and face difficulty recruiting volunteers.

My study also carries practical value. In recent years, the need for better policies to motivate voluntary donation in healthcare has been signified due to the increasing shortages in human blood, organs and tissues (Bergstrom et al. 2009; Kessler and Roth 2012, 2014). My study shows that the additional blood collected using group reward can support more than a good number of additional surgeries. In addition, Rewarding group donors is four times cost effective than rewarding individual donors in motivating blood donation. Such cost is well below the value of having one additional blood unit available. In this way, my study opens a new path to address the above challenge in healthcare using mobile messaging to leverage a donor's social network.

Figures and Tables for Chapter 4 (Essay 3)

Figure 1: Benchmark with C^{sp}=0

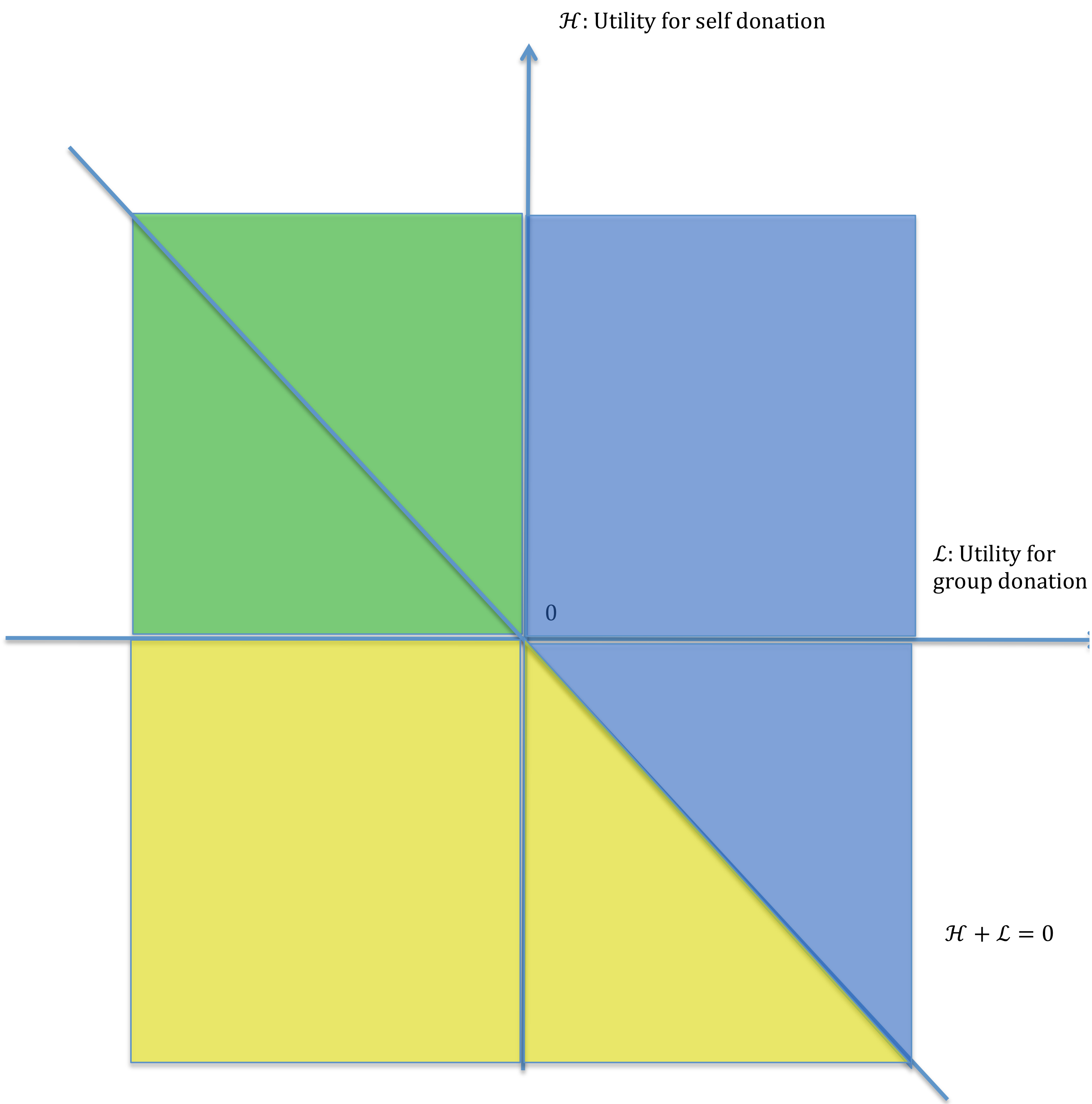


Figure 2: Add $\Delta H > 0$ to Figure 1

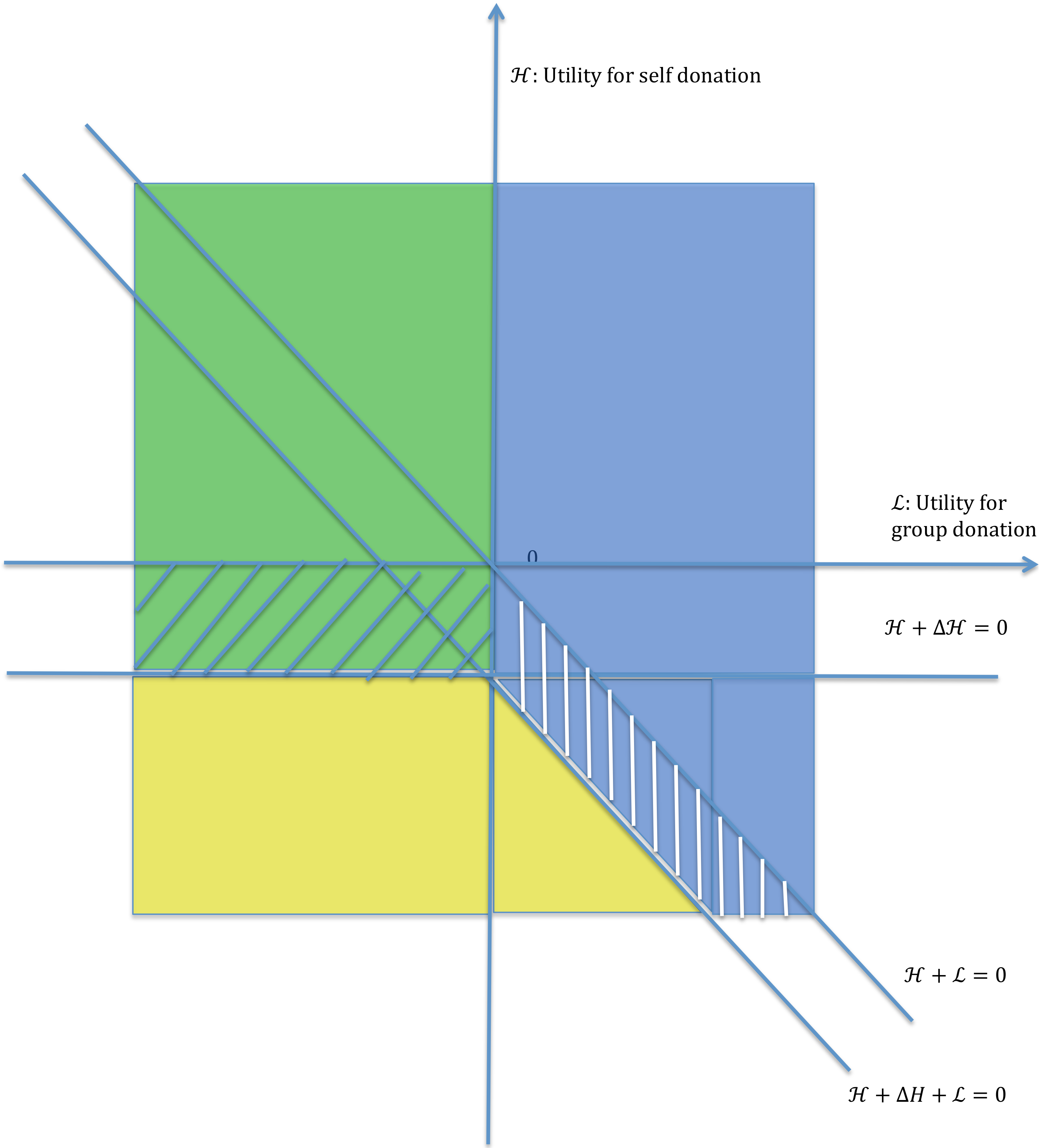


Figure 3: Add $\Delta\mathcal{L} > 0$ to Figure 1

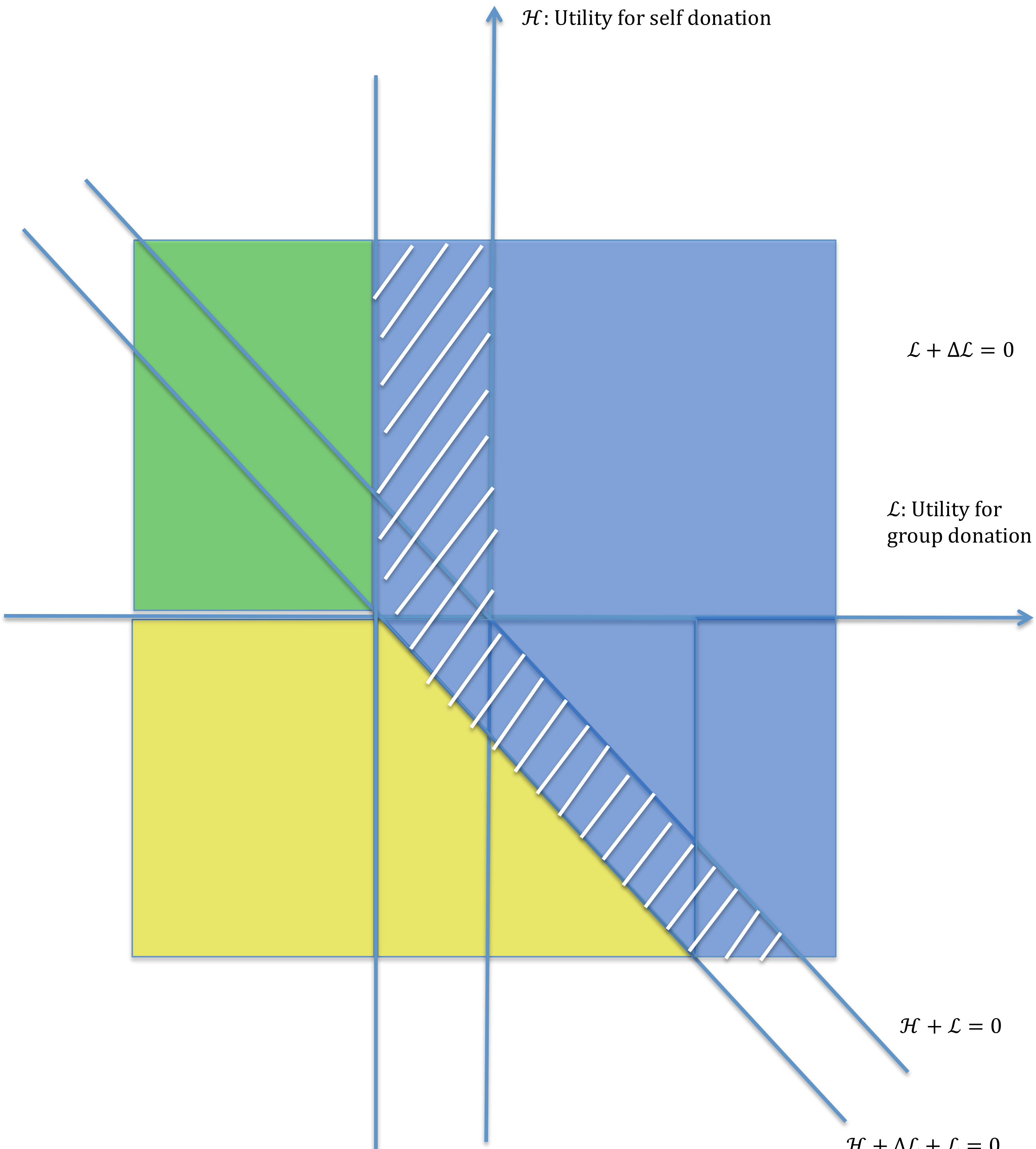


Figure 4: Add $C^{sp}>0$ to Figure 1

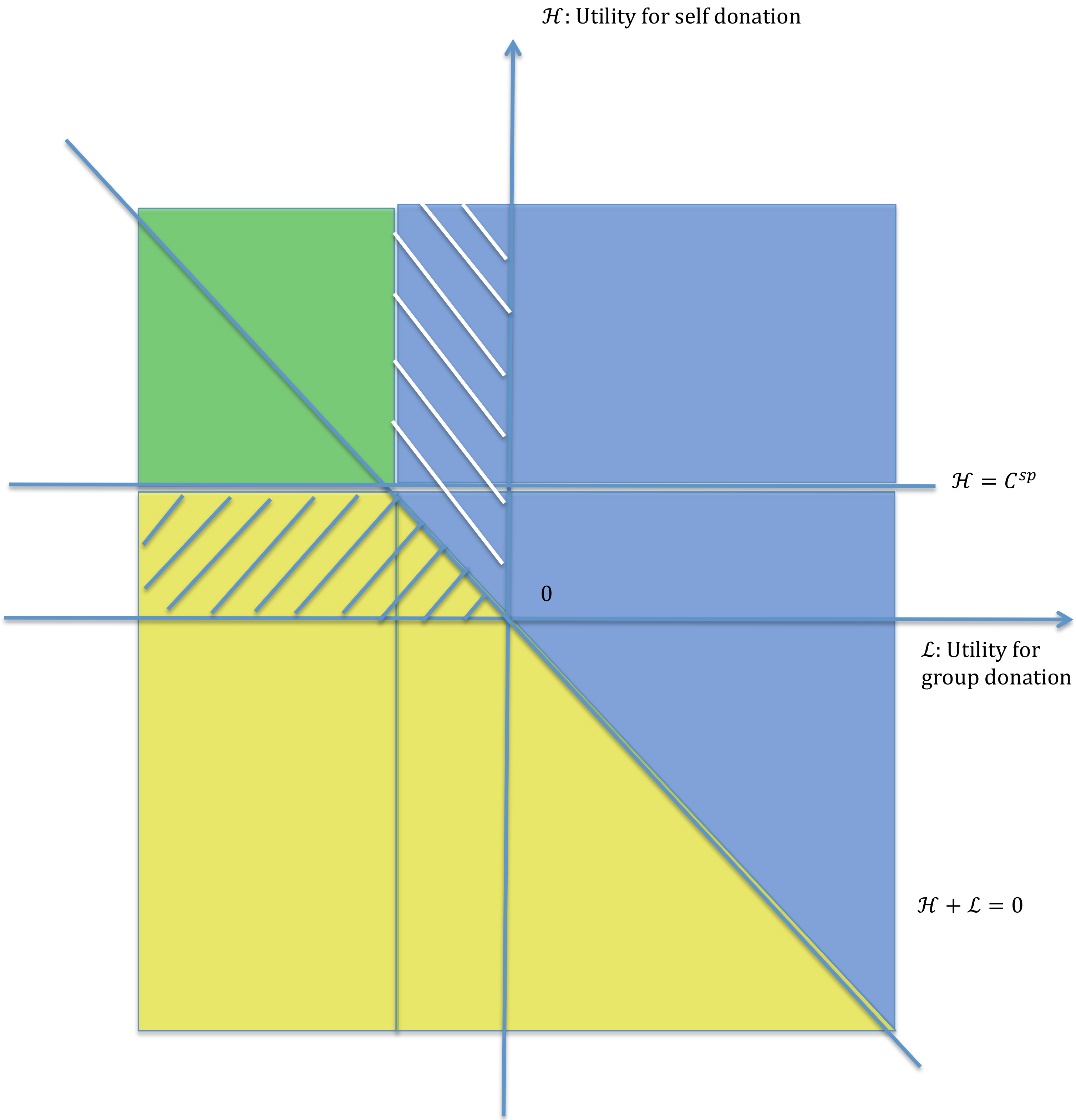
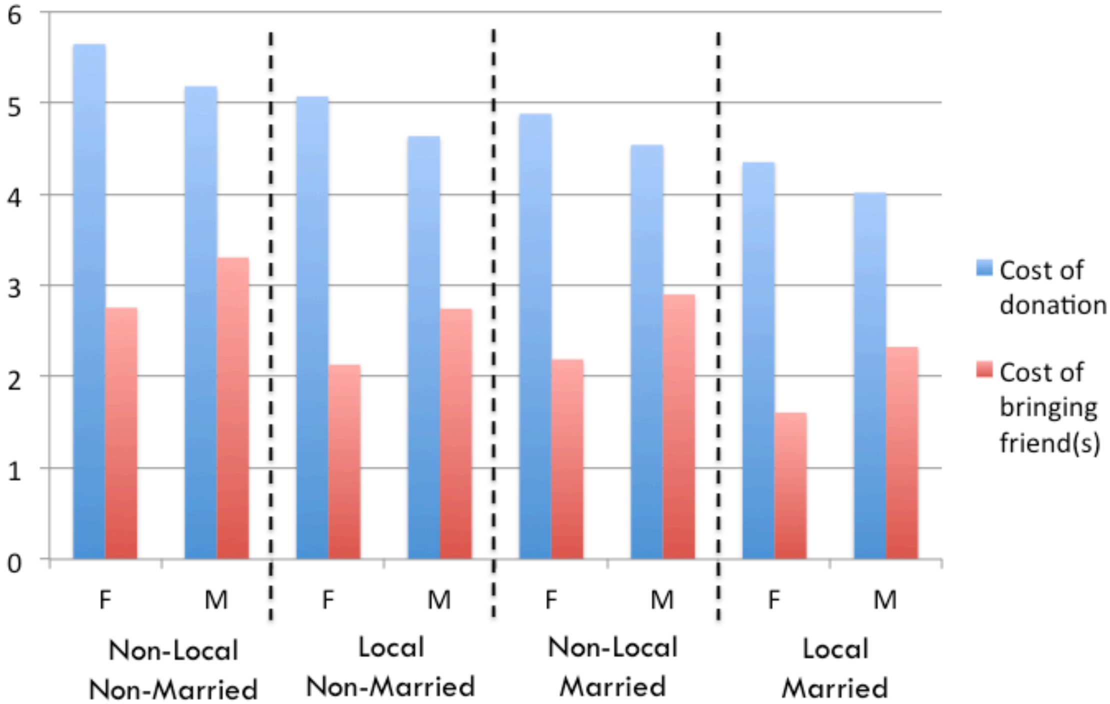
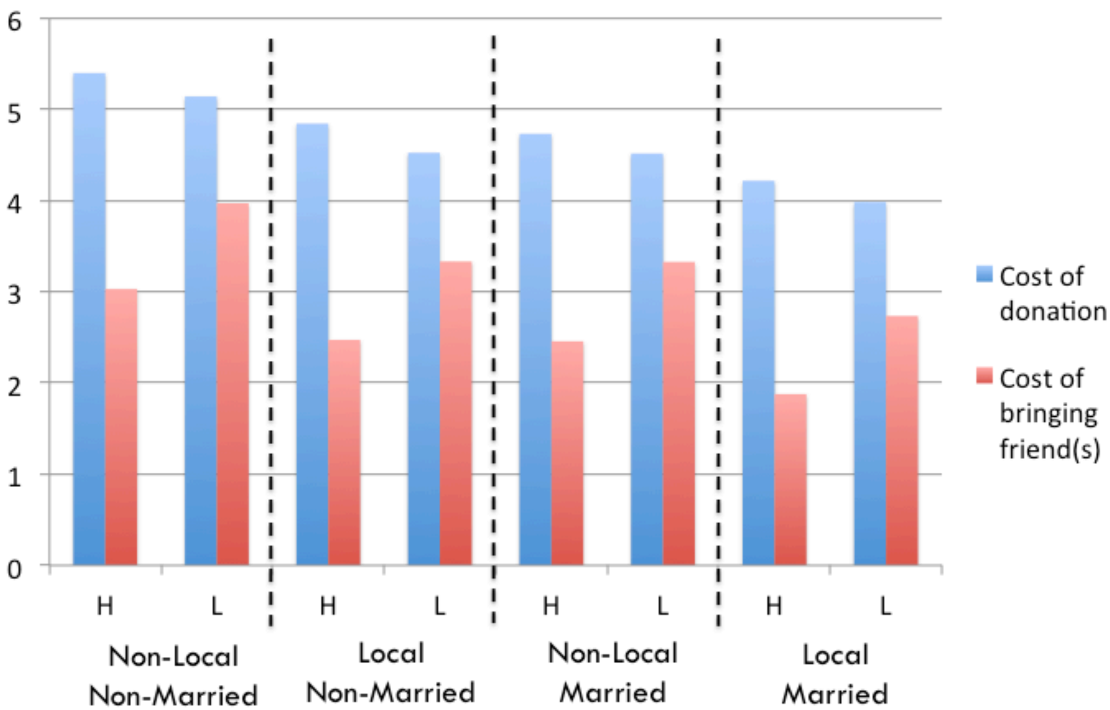


Figure 5: Heterogeneity in both costs across gender, local and marriage status



* F is short for female; M is short for male

Figure 6: Heterogeneity in both costs across education, local and marriage status



* H is short for more educated; L is short for less education

Table 1: Experimental Design

Test Group	Behavior Intervention			Economic Reward		
				Reward for Self Donation	Reward for group donation	
Message Components	Reminder to Donate	Reminder to bring friend			to self	to friend
(Parameter in model)	(DMSG)	(GMSG)	(C^{sp})	(M^{sr})	(M^{gr})	(M^{fr})
T0						
T1	X					
T2	X			X		X
T3	X	X	X			
T4	X	X	X	X		X
T5	X	X	X		X	X
T6	X	X	X	X	X+Small gift	X+Small gift

Table 2: Randomization check

Test Group	Number of subjects	Male	Age (as of 2014)	Married	Local resident	Number of Past Donations
T0	14000	60.6%	27.87	39.3%	38.3%	1.43
T1	11000	60.6%	27.93	39.3%	38.4%	1.44
T2	11000	60.2%	27.96	39.3%	37.8%	1.42
T3	11000	60.9%	27.84	39.7%	37.9%	1.42
T4	11000	60.0%	28.01	39.6%	38.8%	1.44
T5	11000	60.9%	27.85	39.6%	37.9%	1.44
T6	11000	60.8%	27.73	38.6%	38.3%	1.44

Table 3: Summary statistics

Panel A: donation rate and donor demographics

Test Group	Total	Not Donate (%)	Donate (%)	Donor Demographics				
				Male	Age	Married	Local	Number of Past Donations
T0	14,000	13,901 (99.29%)	99 (0.71%)	70.71%	31.25	59.72%	21.21%	2.13
T1	11,000	10,892 (99.02%)	108 (0.98%)	60.19%	31.49	63.41%	19.44%	2.42
T2	11,000	10,880 (98.91%)	120 (1.09%)	65.00%	30.53	57.45%	16.67%	1.92
T3	11,000	10,905 (99.14%)	95 (0.86%)	72.63%	32.02	71.83%	25.26%	2.07
T4	11,000	10,878 (98.89%)	122 (1.11%)	66.39%	31.07	53.68%	24.59%	2.22
T5	11,000	10,871 (98.83%)	129 (1.17%)	63.57%	32.60	65.31%	31.01%	2.55
T6	11,000	10,876 (98.87%)	124 (1.13%)	73.39%	29.99	50.52%	20.97%	2.26
Total	80,000	79,203	797	67.25%	31.26	59.77%	22.84%	2.23

Table 3: Summary statistics

Panel B: Group donation behavior conditional on self donation

Test group	Total number of participants that donate	Solo donation		Donation with non-donating friend(s)		Donate with donating friend(s)	
		%	Amount of Self Donation (ml)	%	Amount of Self Donation (ml)	%	Amount of Self Donation (ml)
T0	99	87.88%	327.59	8.08%	375.00	4.04%	300.00
T1	108	88.89%	345.83	9.26%	380.00	1.85%	250.00
T2	120	84.17%	348.51	9.17%	381.82	6.67%	350.00
T3	95	89.47%	340.00	9.47%	388.89	1.05%	300.00
T4	122	86.07%	352.38	8.20%	390.00	5.74%	385.71
T5	129	83.72%	354.62	5.43%	400.00	10.85%	378.57
T6	124	82.26%	348.03	13.71%	382.35	4.03%	400.00

Table 4: Reduced-form regression results

Panel A: Full Sample with and without demographic controls, linear OLS

Dependent Variable [Sample avg]	Donate or not (1 or 0) [0.0071]		Amount of Self Donation (ml) [2.336]		Amount of Friend Donation (ml) [0.15]		Amount of Self + Friend Donation (ml) [2.486]	
T1	0.00275**	0.00274**	1.073**	1.071**	-0.0864	-0.0868	1.023**	1.020**
T2	0.00384***	0.00379***	1.501***	1.479***	0.105	0.103	1.605***	1.582***
T3	0.00156	0.00171	0.637	0.686	-0.0955	-0.0942	0.542	0.592
T4	0.00402***	0.00399***	1.628***	1.611***	0.114	0.112	1.742***	1.723***
T5	0.00466***	0.00478***	1.882***	1.929***	0.495***	0.503***	2.414***	2.469***
T6	0.00420***	0.00427***	1.664***	1.697***	0.141	0.143	1.842***	1.877***
Male		0.00101		-0.0156		-0.0733		-0.0928
Age		0.000399***		0.177***		0.00980**		0.189***
Weight		0.000118***		0.0521***		0.000889		0.0534***
Test of equivalence (p-value)								
T2=T5	0.541	0.462	0.426	0.350	0.0146	0.0130	0.132	0.100
T3=T5	0.0210	0.0228	0.00945	0.0102	0.000223	0.000220	0.000488	0.000528
T1=T3	0.377	0.442	0.363	0.425	0.955	0.964	0.370	0.428
T4=T6	0.892	0.832	0.940	0.858	0.865	0.849	0.852	0.776
T3=T4	0.0668	0.0902	0.0389	0.0552	0.191	0.201	0.0254	0.0362
N of obs	80000	79,662	80000	79,662	80000	79,662	80000	79,662
R2	0.0003	0.002	0.0003	0.003	0.0002	0.0003	0.0003	0.003

Note: ***p<0.01, **p<0.05, * p<0.1.

Table 4: Reduced-form regression results

Panel B: Conditional on self donation, without demographic controls, linear OLS

Dependent Variable [Sample Average]	Bring donating friend(s) [0.0404]	Amount of Self Donation [330.30]	Amount of Friend Donation [21.21]	Amount of Self + Friend Donation [351.52]
T1	-0.021	16.92	-17.51	-0.59
T2	0.026	21.36**	2.12	23.48
T3	-0.030	13.91	-18.05	-4.15
T4	0.017	27.07***	2.56	29.63
T5	0.068**	29.39***	36.93**	66.31***
T6	-8.15E-05	24.54**	1.37E+04	25.90
Test of equivalence (p-value)				
T2=T5	0.133	0.403	0.0474	0.0369
T3=T5	0.00101	0.13	0.00154	0.000611
T1=T3	0.796	0.777	0.973	0.855
T4=T6	0.543	0.792	0.935	0.832
T3=T4	0.12	0.203	0.185	0.0743
N of Obs	797	797	797	797
R2	0.019	0.014	0.018	0.024

Note: ***p<0.01, **p<0.05, * p<0.1.

Table 4: Reduced-form regression results

Panel C: subsamples by last donation time

Last Donation	Top Quartile (within recent 9 months)			Second Quartile (within 10-14 months)			Bottom Half (more than 14 months)		
Dependent Variable	Amount of Self Donation (ml)	Amount of Friend Donation (ml)	Amount of Self+ Friend Donation (ml)	Amount of Self Donation (ml)	Amount of Friend Donation (ml)	Amount of Self+ Friend Donation (ml)	Amount of Self Donation (ml)	Amount of Friend Donation (ml)	Amount of Self+ Friend Donation (ml)
T1	2.036*	-0.250	1.920	1.519	-0.102	1.414	0.334	0.00150	0.336
T2	2.703**	-0.0132	2.690**	2.177**	0.297	2.473**	0.429	0.0739	0.503
T3	2.172*	-0.349	1.822	-0.00429	-0.129	-0.133	0.0381	0.0557	0.0938
T4	3.613***	0.237	3.850***	1.512	0.164	1.673	0.412	0.000507	0.413
T5	4.279***	0.942**	5.352***	1.769*	0.105	1.872	0.635	0.432***	1.067**
T6	4.257***	0.321	4.578***	1.171	0.0581	1.383	0.475	0.0742	0.549
Male	-0.223	0.294	0.132	1.134	-0.423*	0.630	-0.202	-0.0885	-0.291
Age	0.462***	0.0239*	0.487***	0.115***	0.0212**	0.143***	0.0674***	-0.00207	0.0653***
Weight	0.0385	-0.0201	0.0183	0.0422	0.00573	0.0498	0.0428***	0.00878*	0.0516***
Test of equivalence (p-value)									
T2=T5	0.194	0.0210	0.0522	0.713	0.562	0.623	0.659	0.0334	0.278
T3=T5	0.0836	0.00190	0.0104	0.109	0.482	0.100	0.204	0.0264	0.0630
T1=T3	0.912	0.813	0.944	0.166	0.936	0.203	0.526	0.748	0.642
T4=T6	0.599	0.840	0.600	0.756	0.747	0.810	0.892	0.659	0.791
T3=T4	0.238	0.160	0.142	0.167	0.374	0.136	0.424	0.744	0.541
N of obs	21,796	21,796	21,796	18,619	18,619	18,619	39,247	39,247	39,247
R2	0.009	0.001	0.008	0.002	0.001	0.002	0.001	0.000	0.001

Note: ***p<0.01, **p<0.05, * p<0.1.

Table 5: Donation amount and friend presence

Sample = Subjects in the experiment and donate

Dependent Variable [Sample Average]	Amount of Self donation [326.68]		
	(1)	(2)	(3)
T1	17.21*	13.57	12.31
T2	20.28**	22.36**	19.57**
T3	14.37	11.06	10.90
T4	26.55***	27.81***	24.81***
T5	28.18***	25.15***	24.51***
T6	22.90**	26.36***	22.68***
1(if come with friend)	29.14***	31.85***	26.53***
Male		-22.44***	-22.80***
Age		2.552***	2.083***
Weight		1.204***	1.291***
Local Resident			4.306
Married			-9.454
Observations	797	797	797
R2	0.032	0.211	0.288

Note: ***p<0.01, **p<0.05, * p<0.1.

Table 6: Heterogeneous Treatment Effects

Dependent Var.	Donate or Not				Amount of Self + Friend Donation			
Demographic Dummy	Married	Local	Age>35	Past Donation>2	Married	Local	Age>35	Past Donation>2
T1	0.00151	0.00272**	0.00238*	0.00150	0.439	1.024*	0.879	0.595
T2	0.00276*	0.00404***	0.00397***	0.00387***	1.110*	1.574***	1.564***	1.683***
T3	8.40e-07	0.000993	0.00129	0.00143	-0.0503	0.336	0.388	0.581
T4	0.00351**	0.00322**	0.00401***	0.00309**	1.450**	1.372**	1.718***	1.310**
T5	0.00270*	0.00294**	0.00235	0.00259*	1.362**	1.744***	1.448**	1.441***
T6	0.00397***	0.00386***	0.00458***	0.00327**	1.657***	1.598***	1.786***	1.526***
Demo Dummy	0.00574***	0.00447*	0.00647***	0.0145***	2.232***	1.825*	2.607***	6.596***
T1 x demo	0.00429	0.000174	0.00161	0.0122***	2.032*	-0.0151	0.632	4.137**
T2 x demo	0.00374	-0.00136	-0.000582	-0.000274	1.738	0.284	0.203	-0.834
T3 x demo	0.00529*	0.00439	0.00135	0.00223	2.009*	1.586	0.744	-0.127
T4 x demo	0.00169	0.00597	-1.92e-05	0.00964**	0.970	2.750*	0.0822	4.458**
T5 x demo	0.00665**	0.0123***	0.0107***	0.0217***	3.592***	4.812***	4.467***	10.22***
T6 x demo	0.000901	0.00251	-0.00154	0.00994**	0.663	1.794	0.364	3.371*
N of Obs	80,000	80,000	80,000	80,000	80,000	80,000	80,000	80,000
R2	0.001	0.001	0.002	0.005	0.001	0.001	0.002	0.006

Notes: Columns for Married control for the dummy variable that indicates missing values in Married. ***p<0.01, **p<0.05, *p<0.1

Table 7: Survey Responses

Panel A: Responses across test groups

Test Group	Ever hear your friends donate?		Will you share this donation experience?		Willing to bring friend next time?		
	No	Yes	No	Yes	No	Yes	Not Sure
0	16 32.65%	33 67.35%	8 16.33%	41 83.67%	5 10.42%	27 56.25%	16 33.33%
1	13 23.21%	43 76.79%	14 23.33%	46 76.67%	15 25.42%	29 49.15%	15 25.42%
2	10 16.67%	50 83.33%	9 16.36%	46 83.64%	7 11.11%	34 53.97%	22 34.92%
3	10 25%	30 75%	10 24.39%	31 75.61%	8 18.18%	20 45.45%	16 36.36%
4	11 20.75%	42 79.25%	8 15.69%	43 84.31%	8 14.81%	32 59.26%	14 25.93%
5	13 19.7%	53 80.3%	10 15.15%	56 84.85%	7 10.14%	44 63.77%	18 26.09%
6	24 37.5%	40 62.5%	19 31.67%	41 68.33%	13 19.4%	26 38.81%	28 41.79%
Total	97 25%	291 75%	78 20.42%	304 79.58%	63 15.59%	212 52.48%	129 31.93%

Panel B: Responses between donors who come with friend and donors who come without friend

	Ever hear your friends donate?		Will share donation experience?		Willing to bring friend next time?		
	No	Yes	No	Yes	No	Yes	Not Sure
Without Friend	92 28.57	230 71.43	73 23.03	244 76.97	56 16.92	166 50.15	109 32.93
With Friend	5 7.58	61 92.42	5 7.69	60 92.31	7 9.59	46 63.01	20 27.4

Table 8: Structural Estimates for First Stage Decision (none, solo, group donation)

Base outcome: Do not donate

Panel A: Individual Primitives and the Effect of Interventions
(Alternative-Invariant Coefficient)

	Coefficient	Standard Error
Net Utility from Donation	-5.84	0.14
Net Utility for Bringing Friend(s)	-2.81	0.50
Reminder for self-donation	0.31	0.13
Social Pressure for solo donation after receiving reminder for bringing friend(s)	0.02	0.08
Reminder for Bringing Friend	-0.52	0.42
Reward to subject for self-donation	0.10	0.08
Reward for subject's friend donation	1.01	0.46
Reward to subject for group donation	1.11	0.41

Panel B: Individual Demographics (Alternative-Specific Coefficient)

Solo Donation Alternative	Coefficient	Standard Error
Male and Weight in Upper Half	0.07	0.09
Female and Weight in Upper Half	0.58	0.14
Male	0.51	0.10
Current Age >33	0.24	0.09
Married	0.56	0.10
Local Resident	0.50	0.09
Education <=9 years	0.17	0.10

Group Donation Alternative	Coefficient	Standard Error
Male and Weight in Upper Half	-0.20	0.49
Female and Weight in Upper Half	0.68	0.44
Male	-0.37	0.40
Current Age >33	0.23	0.42
Married	0.53	0.44
Local Resident	0.54	0.38
Education <=9 years	-0.97	0.62

Table 9: Structural Estimates for Second Stage Decision (200ml, 300ml, 400ml)

Base outcome: Donate 200ml

Panel A: Individual Primitives & Effect of the Presence of Friend(s)

	Coefficient	Standard Error
Net utility from donating 300ml	1.18	0.39
Net utility from donating 400ml	1.50	0.37
Donating 300ml with the presence of donating friend(s)	0.86	0.69
Donating 300ml with the presence of non-donating friend(s)	1.99	1.07
Donating 400ml with the presence of donating friend(s)	0.86	0.66
Donating 400ml with the presence of non-donating friend(s)	2.86	1.03

Panel B: Individual Demographics (Alternative-Specific Coefficient)

Solo Donation Alternative	Coefficient	Standard Error
Male and Weight in Upper Half	0.30	0.31
Female and Weight in Upper Half	-0.36	0.61
Male	-1.30	0.38
Current Age >33	-0.66	0.42
Married	0.52	0.43
Local Resident	0.35	0.43
Education <=9 years	1.18	0.67

Group Donation Alternative	Coefficient	Standard Error
Male and Weight in Upper Half	0.67	0.27
Female and Weight in Upper Half	0.63	0.56
Male	-0.81	0.36
Current Age >33	0.55	0.35
Married	0.47	0.38
Local Resident	0.68	0.37
Education <=9 years	2.01	0.61

Table 10: Policy Simulation

	Average Prob. of Subject Coming for Solo Donation (1)	Average Prob. of Subject Coming for Group Donation (2)	Total Number of Donors (1)+(2)*2	Total Unit of Reward to the Donors	Reward per Donor
No treatment	0.69%	0.02%	0.73%	0.00%	0.00
Reminder for self-donation	0.94%	0.03%	0.99%	0.00%	0.00
Reminder for self-donation + Reminder for bringing friend(s)	0.97%	0.02%	1.00%	0.00%	0.00
Reward to subject for self-donation (SR)	1.03%	0.03%	1.09%	1.06%	0.97
Reward for subject's friend donation (FR)	0.97%	0.04%	1.05%	0.04%	0.04
Reward to subject for group donation (GR)	0.97%	0.05%	1.06%	0.05%	0.04
SR + GR	1.06%	0.05%	1.16%	1.16%	1.00
FR + GR	0.97%	0.13%	1.22%	0.26%	0.21
SR + FR	1.06%	0.05%	1.15%	1.15%	1.00
SR + FR + GR	1.06%	0.14%	1.34%	1.48%	1.10
SR (1.5 Unit)	1.09%	0.03%	1.15%	1.12%	0.97
SR (2 Unit)	1.15%	0.03%	1.21%	1.18%	0.97
FR (1.5 Unit) + GR (1.5 Unit)	0.95%	0.36%	1.67%	0.72%	0.43
FR (2 Unit) + GR (2 Unit)	0.96%	1.04%	3.04%	2.08%	0.68

Chapter 5: Conclusion

My dissertation seeks to examine the optimal design choices for firms seeking to engineer digital sharing platforms and maximize returns from information sharing. Specifically, I study novel interventions that can be implemented by the platform at different stages of information sharing process. In collaboration with a for-profit platform and a non-profit platform, I conduct three large-scale field experiments to causally identify the impact of these interventions on customers' sharing behaviors as well as the sharing outcomes.

The first essay examines whether and how a firm can enhance social contagion by simply varying the message shared by customers with their friends. Despite its central importance in creating social contagion, there is very little understanding of how different components of a message impact social contagion. My study is among the first to address this issue by examining granular aspects of the message and their differential impacts on the outcomes of social contagion in the context of online purchase behaviors of individuals. Using a large randomized field experiment, I find that small variations in message content can have a significant impact on both recipient's purchase and referral behaviors. In my case the message containing only information about the sender's purchase outperforms all the other message designs and is recommended as the optimal message design for the firm. Based on the results of my field experiment, the implementation of optimal message design leads to significant increase in net profits, even after accounting for the cost of referral rewards. The increased profits far outweigh the costs for the field experiment and implementation. Interestingly, I also find evidence that the same message design is also optimal from the customer welfare perspective, as it reveals product information and facilitates coordination.

The second essay studies whether and how a firm can design unconditional incentive (i.e. varying the number of promo code and whether it can be shared) to engage customers who already reveal willingness to share but did not purchase themselves. Using a large field experiment, I examine the impact of incentive design on sender's purchase as well as further referral behavior. I find evidence that incentive structure has a significant impact on both outcomes, but in a different way.

The third essay examines whether and how a non-profits can design group incentive to motivate donors to donor in a group. I design a large field experiment to causally identify the impact of different types of information and incentives on donor's individual and group donation behavior. My results show that non-profits can stimulate group effect and increase blood donation, but only by providing appropriate economic incentives.

In summary, the findings from the three studies will provide valuable insights for platforms and social enterprises on how to engineer digital platforms to create social contagion. The rich data from randomized experiments and archival also allows me to test the underlying mechanism at work. In this way, my dissertation provides both managerial implication and theoretical contribution to the phenomenon of peer-to-peer information sharing.

While the design of messages and incentives is often open-ended and done in an ad-hoc fashion, my study demonstrates how to use field experiments in a networked environment to identify the causal impact of different design of messages or incentives. In this way, my study paves the way for a more structured approach for engineering digital sharing platform to create social contagion. Based on the context and the nature of the product, other components of the message or other types of incentive may be important in driving the effectiveness of information sharing in driving social contagion. However, the empirical framework in my studies could still apply.

Putting together, the three studies in my dissertation have shown that firms can engineer digital sharing platforms to amplify the advantages of information sharing and create social contagion. All studies are proof-of-concept of a central theme: firms can apply centralized interventions on decentralized sharing process thus enjoy the benefits of the both information provision paradigm. Small changes to the information sharing process can be accomplished with very little cost and promise substantial gains to the firm.

Looking forward, my dissertation can be extended in three ways. First the proposed interventions in my dissertation is complementary to other traditional and social marketing approaches such as price discrimination, targeting influencers (Manchanda et al. 2008), network seeding (Hinz et al. 2011), viral product design (Aral and Walker 2011a), viral content design (Berger and Milkman 2012), and referral programs (Schmitt et al. 2011), among others. It would be valuable to examine how the proposed interventions complement these traditional approaches. I hope that my studies serve as a first step in that direction.

Second, identifying optimal intervention at aggregate level is a useful first step. With the availability of large amount of data on sender and recipient behaviors and their historical interactions, as well as the ability to process requests in real time, firms can actually personalize intervention at a subgroup or even individual level. While personalization is a common practice in the context of firm-customer interactions, personalization of customer-customer social interactions is still in its infancy. As an important step in this direction, my dissertation examines various moderators to shed light on the variations in treatment effect for different types of senders, recipients, strength of ties, and products. I envision that in the near future when a firm gets a request of email share from a sender, it would leverage historical information to extract product characteristics, sender and recipient's purchase and interaction histories, calculate optimal content and message design, and deliver the message in real time in a personalized fashion. My work serves as a valuable proof-of-concept of this impending development.

Finally, firms or social planner can apply centralized interventions into other types of social interactions. Besides information sharing, interpersonal behaviors such as gifting, renting, managing and mentoring also constitute a large portion of social life and impact huge volume of economic transactions. They are increasingly mediated by digital platforms. Optimal design of centralized interventions for those interpersonal behaviors would have a profound impact on human life.

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