Does Care Lead to Share? Evidence from a Randomized Field Experiment on Call for Sharing

Completed Research Paper

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Abstract

Information sharing through online WOM has become increasingly important for businesses. Despite the popularity of online referral programs, little is known about how firms can optimally design call-to-action to encourage referrals, as well as the motives underlying those referrals. In collaboration with a large US based online platform specialized in photo processing, we conduct a large randomized field experiment involving 100,000 customers to identify the causal effect of three types of call-to-action for referral (egoistic, equitable and altruistic) that are widely used in practice. Our experiment shows that, surprisingly, 'altruistic' call-to-action leads to highest likelihood of referral and best referral outcomes. Such altruistic framing is more effective for customers who had repeated purchases in the past and who reported higher Net Promoter Score. Also, we find that the effect of altruistic framing decays fast after customer's purchase. In this way, our study provides direct managerial implications to firms on the optimal design of call-to-action for referral campaigns (how, to whom and when to send call-to-action for referral). We also show that altruism is an important driver of online referral among customers and how such motive leads to referral decision and referral outcomes. Finally, we discussed the key differences and complementarity between call for referral and call for purchase, and offer guidance on firm's integrated marketing communication strategy.

Keywords: Field experiment, Online referrals, Altruism, Social contagion, Call-to-action

Introduction

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

A close look at influential referral programs in the practice[2] reveals that there are three types of call for sharing to the customer who may initiate referrals (i.e. 'sender'): a) the 'egoistic' call for sharing action, where the firms highlight the reward to the sender, b) the 'equitable' call for sharing action, where the firms highlight that both sender and her friends can get the reward, and c) the 'altruistic' call for sharing action, where the firms highlight the reward to the friends. Among all three types of call for sharing, the 'altruistic' call is least observed, potentially driven by firms' perception that the sender may be more likely to initiate a referral if her own, ostensibly monetary, benefit is highlighted. However, previous literature has shown that individuals may derive significant non-monetary payoff from helping others in the form of either warm glow or pure altruism, see Andreoni 1988, 1990. Thus, the altruistic call may enhance customers' pure altruism or warm glow therefore encourage more sharing from them. In addition, the altruistic call may reduce customers' psychological cost of feeling guilty about gaining referral rewards (Rue and Feick 2007). Given above considerations, it is an empirical question as to which type of call-to-action is most effective for overall referral marketing, one we tackle via a randomized field experiment.

In this study, we aim to identify the optimal call for sharing action. In collaboration with a large US based online platform specialized in photo processing, we conduct a large randomized field experiment involving 100,000 customers to test the impact of three different call for sharing, as discussed above. We fix the incentive design of the referral program as equal-split[3] and only vary the call for sharing to the senders in our experiment. We are interested in identifying the causal effect of call for sharing on customers' sharing decision (whether to share and with whom to share) as well as on their sharing outcomes (number of successful referrals, number of new users). Specifically, we answer the following questions:

- Optimal design: Which type of call for sharing is most effective in increasing the volume and effectiveness of WOM referrals?
- Targeting strategy: Is a certain type of call for sharing more effective for a certain group of customers?
- Timing: Does the effect of call for sharing change over time?
- Underlying mechanism: Why certain types of call for sharing work better? Can firms gain insights on the motives of customers to send out referrals?

We are particularly interested in the role of altruistic framing[4] in driving customer's sharing decision and related outcomes. While conventional wisdom, and the observed norm in practice, is to emphasize the benefit of the referral incentive to the sender to stimulate their act of referring, there is reason to believe that this can be counter-productive. As discussed above, customers may derive non-monetary payoff if they care about friends' payoff (pure altruism) or about the sharing action itself (warm glow). If altruism plays

[1] Source: blog.talkable.com

[2] Please see an excellent summary of influential referrals programs (http://www.referralcandy.com/blog/47-referral-programs/)

[3] Equal-split incentive is widely adopted in practice and has been shown to have better performance than other types of incentive design (Bapna et al. 2014)

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

an important role in sharing behavior, then we would expect the altruistic call might significantly increase a sender's likelihood of sharing since the aligned framing enhances his/her altruistic feelings. However, if the argument of the friend's interest is taken a step further, it can be the case that the existing customer will become more selective in sharing as they care and deliberate more about friend's payoff from purchasing the focal product (Kornish and Li, 2010). Thus, the altruism call might also lead to fewer shares by the senders because it becomes harder for them to identify potential recipients. This potential downside however can be counter-balanced by the fact that that conditional on the sharing decision, such selective shares driven by altruism may result in higher conversion rate than those driven by other motives, such as the equitable and selfish). Given the above tradeoffs, it is not clear whether altruism would always lead to more shares and better sharing outcomes. Our experiment is among the first to directly test the role of altruism in driving information sharing in the referral marketing process.

Our analysis is based on a large-scale field experiment we implemented in partnership with an e-commerce site. We collected data on customers' sharing decision and outcomes within a 5-week window after the experiment. We further augmented the data from field experiment with rich archival data, including product characteristics, individual characteristics, past purchases as well as net promoter score (hereafter, NPS) (e.g. willing to share the product). We also conduct a post-experiment survey to understand why customers in our experiment share/not share after receiving the call-to-action. The data from randomized experiment, archive and survey allows us to identify the causal effect of different call for sharing as well as to explore the underlying mechanisms.

Our primary finding, consistent across multiple econometric specifications, is that, in contrast to conventional wisdom, the altruistic framing of the call-to-action for initiating a referral is most effective in driving sharing behavior resulting in better outcomes for the firm. Compared to the control group, the email that highlights friends' reward significantly increases not only the likelihood of sender making referrals, but also the total number of successful referral purchases. In addition, we find that the effect of altruistic framing is significantly higher than the effect of egoistic framing and equitable framing across almost all the sharing outcomes. Our results suggest that firms should use altruistic framing more in their call for sharing than is the current practice. Secondly, we find heterogeneous treatment effects in that the altruistic framing is more effective for users who made repeat purchase in the past and who reported higher NPS score (Reichheld 1996). This is aligned with the notion that customers who have higher levels of product and brand affinity are more likely to share it with their friends because of altruism as they care about the friend's utility. Thus, given the costs associated with referral marketing, firm should target those customers first in their call for sharing campaign. Additionally, we find that the effect of altruistic framing to initiate sharing decays at a faster rate relative to the other framing schemes after the customers' last transaction. The result suggests that firms should send out an altruistic call for sharing to customers shortly after their purchase, at which point they are most enthusiastic about the product. Finally, the results from the post-experiment survey suggest that altruistic call for sharing is associated with a reduction in customers' feeling of guilt in making referrals but is not linked with the perceived difficulty of finding a friend who may like the product compared to egoistic and equitable call for sharing. We also find that customers who are under altruistic framing are more likely to report that "friends/family might happy with the promotion" as their motive of sharing. Overall, the evidence suggests that altruism is important in driving information sharing and it can be spurred by altruistic call for sharing.

Our findings also provide guidance for companies on how to engage customers with two different call-to-action: call for sharing and call for purchase. Call for sharing is usually sent out to customers in the form of digital marketing communication (e.g. through electronic email and mobile messages). Given the limited bandwidth of marketing communication due to limited attention of customers, it is important and interesting to compare call for sharing with call for purchase (promotional advertising), which is the dominant forms of marketing communication from a firm. Based on the results from our experiment, we identify three types of differences between the two forms of communication. First, for durable goods like printed products we studied in this paper, call for purchase is in general not effective immediately after purchase. However, our results provide evidence that this may be the best time to engage customers with call for sharing. Second, promotional email is more effective when targeted to less loyal customers in call for purchase. However, in call for sharing, promotional email highlighting the reward to a friend is most effective for loyal customers because of altruism. Finally, while call for purchase is always highlighting customer's own benefits, optimal design for call for sharing should highlight the benefits of one's friend. Interestingly, all the three differences (timing, targeting and design) make ('altruistic') call for sharing complementary with the call for purchase in marketing communication. Thus firms can optimally combine them to form an integrated communication strategy and engage customers in their lifecycle.

In summary, our study, using a large-scale randomized field experiment involving 100,000 customers, provides direct managerial implications for firms to design optimal call for sharing (how, whom and when to send out call for sharing). In this way, we close the gap in the literature on the optimal design of referral program. Theoretically, our study is also among the first to show that altruism is an important driver of information sharing among customers in the context of referral marketing and how such motive leads to sharing decision and sharing outcomes. Finally, we have discussed the difference between call for sharing and call for purchase and found the two forms of marketing communication are complementary in timing, audience and motives.

The remainder of the paper is structured as follows. In section 2, we review related literature and specify our contribution. In section 3, we describe our experimental design and data. Then we present our empirical strategy in section 4 and results in section 5. Finally, we draw conclusions in section 6.

Literature review

Our study draws and complements three streams of IS and digital marketing e-business research: first, we enrich the literature on the optimal design of referral program by identifying the causal effect of call for sharing. Our study complements recent research on the impact of incentive structure on product diffusion (Bapna et.al. 2014) as well as the effect of message design (Sun et al. 2014). Rather than varying incentive structure or message design, we examine how firms can optimally frame given incentive scheme in call for sharing to motivate individuals to make referrals. The study also joins a large literature addressing opportunities available to the firm for influencing the social interaction among individuals, including viral product design (Aral et al. 2011), mobile advertising (Ghose et al. 2015), Firm-created WOM (Godes and Mayzlin 2009), product policy (Godes 2015), promotional chat (Mayzlin et al. 2006), privacy control (Burtch et al. 2015) and so on.

Second, in this study we aim to provide insights on understanding the underlying motives of senders' information sharing. Although there had been extensive studies on referral reward program, very few studies have proposed motives for transmitting WOM when reward is involved. Rue and Feick (2007) have provided evidence that senders may be influenced by both economic motives and the social risks of referral rewarded. Sun et al. (2015) have identified three primary motives underlying a user's sharing behavior: self-regarding motive (sender's interest in the product), other-regarding motive (sender's interest in the recipient), or group-regarding motive (sender's interest in purchasing the product with the recipient). While it is understood that these varying motives could lead to very different sharing behavior and outcomes with differing implications for firms' strategies, no study has empirically examined this issue. To get a clear understanding of the underlying motives behind sender's sharing behavior, we also conduct a post-experiment survey to understand participants' motive for sharing/not sharing.

Finally, we extend the stream of literature on promotional advertising. Also, rather than focusing on converting the customers, we examine how firms can influence customers to spread WOM through design of call for information sharing. We find that call for sharing is fundamentally different from promotional advertising across a few aspects (in timing, audience and motives). Such differences make the two forms of marketing communication are complementary.

Experiment design and data

Our initial idea of the experimental design comes from both the practice as well as seminal research in economics that categorizes individuals into three categories based on their self and other regarding preferences (see, for instance, Andreoni and Miller 2002). In the paper, the authors showed that individuals are either purely self-regarding, or they care about others only as much as they care about themselves, or their preferences are substitutable between themselves and others. In line with this finding, we test the effect of three different call for information sharing: a) the egoistic call for sharing action, where we highlight the reward to the sender, b) the equitable based call for sharing action, where we highlight that both sender and the receiver get the reward, and c) the altruistic call for sharing action, where we highlight the reward to the receiver.

We conduct a randomized field experiment in collaboration with a large US based online platform specialized in photo processing and related products. On the platform, users can easily design a collage using online software tools. Once a user creates the collage, she can purchase various types of customized printed products, including blankets, photo-books, canvases, etc. A large number of customers purchase a variety of products in the platform every day (with annual revenue more than 22 million USD).

For the experiment, we randomly draw 100,000 unique customers who have purchased products in the previous 4 months, and randomly assign them into one of the four test groups as per Figure 1. Then, we target the customers in the different groups with emails that only vary in their call-to-action for initiating the referral process. In each email, we change the email's title, highlight different aspects of the rewards in the given context, and use different words in the call-to-action button. Once the customers open and click on the 'share' button in the email, they are directed to webpages with the identical framing where they can send a referral to their friends. It is important to note that the identical incentive scheme was offered to all participants across groups where both the sender and receiver get equal reward (70% discount coupon). To reiterate, we create four versions of emails and webpage by only varying the framing of the same incentive scheme, namely, the equal-split incentive scheme in which both sender and receiver get the identical reward.

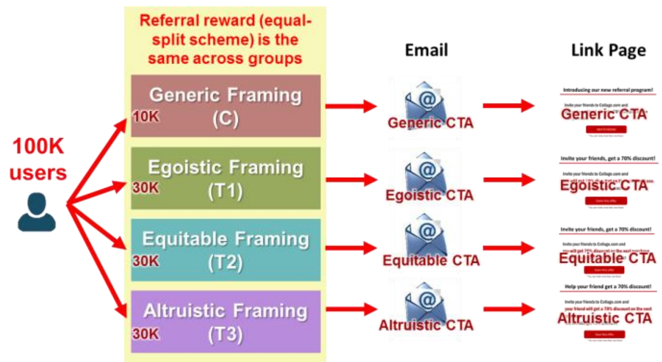

Figure 1: Illustration of the Experiment Design

As the treatment in our experiment was framed messages sent by email, customers, who have selected to unsubscribe future email from the company at the time of their previous purchase were excluded in the analysis. This was the first time the company launched the referral program. Thus, we were able to frame the initial information about the referral program provided to the users. Figure 2 describes the different framing used in the experiment.

Group	Subject and content of the email/link page	Group	Subject and content of the email/link page
No framing (C)	Subject: **The Collage.com Referral Program** Contents: Invite your friends to try Collage.com and you'll both get a 70% discount on your next order. Invite a Friend	Egoistic Framing (T1)	Subject: **Invite your friends, and get yourself 70% off** Contents: Invite your friends to Collage.com and **get a 70% discount on your next purchase.** Your friend will also get 70% discount! Claim This Discount
Equitable Framing (T2)	Subject: **70% off for you and a friend!** Contents: Invite your friends to Collage.com and **you and your friend both will get 70% discount** on the next purchase. Share This Discount	Altruistic Framing (T3)	Subject: **Give your friend a 70% discount!** Contents: Invite your friends to Collage.com and **your friend will get a 70% discount on the next purchase.** You will also get 70% discount! Give This Discount

Figure 2: Email Received by Each User in Different Treatment Groups

The emails were sent out at same day, at the same time, only once to each customer in the experiment. Each customer had a week to send a referral to their friends. Once a customer sends a referral, a 70% discount coupon, which was valid for 30 days, was sent to both the sender and the receiver.

The randomization was orchestrated after the customers' previous purchase and thus, the call for sharing in the email is orthogonal to the customers' previous purchase behavior. Any difference in the customers' sharing decision and outcomes can therefore, be solely and directly attributed to the difference in the received call-to-action for initiating the referral process. We observe several outcomes from the experiment. First, we look at a binary indicator of whether a sender sent a referral. Second, we look at the total number of referrals sent by sender. Lastly, we check the number of recipients' purchases per sender. All three outcomes are closely inter-related, as the sharing behavior is endogenous. The first two outcomes characterize the sharing behavior, whereas the last outcome characterizes the sharing outcome.

Empirical strategy

To identify the effect of different calls-to-action on senders' referral behavior and referral outcomes, we run the regression at the sender level with and without controls. First, we relate the outcome variables to dummy indicators of each of our treatment groups and employ linear probability models and ordinary least squares (Equation 1). Our main estimation equation for sender i is

$$Y_i = \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \varepsilon_i \quad (1)$$

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

Additionally, we augment our field experiment data with survey and archival data and employ linear probability models and ordinary least squares (Equation 2).

$$Y_i = \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \beta_4 \times Survey_i + \beta_5 \times NPS_i + \beta_6 \times WeeksSinceLastPurchase_i + \beta_{numpurchase,category\ k} \times NumPurchase_{category\ k\ i} + \beta_{spending\ category\ k} \times Spending_{category\ k_i} + \beta_{dailydeal\ category\ k} \times DailyDealPurchase_{category\ k_i} + \varepsilon_i \quad (2)$$

Using this model, we aim to evaluate the robustness of the treatment effect as well as to explore the impact of customer affinity (i.e. NPS score and past purchase behavior) and timing of call-to-action (i.e. elapsed time since last purchase) on referral decisions and outcomes. NPS_i indicates the reported NPS score of each sender i. The collaborating platform conduct surveys to collect NPS score (intention of spreading word-of-mouth) of the customer after each purchase. The data of NPS scores collected prior to the experiment allow us to estimate the main effect as well as the moderator effect of NPS score on the referral behaviors and outcomes. In our experiment, 23% of the users had reported their NPS score prior to the experiment. We also include a survey response dummy variable (e.g. $Survey_i$) as a control, which would account for situations when NPS score information is missing.

In addition, we measure the recency of a sender's purchase using $WeeksSinceLastPurchase_i$, i.e. the number of weeks that have elapsed between the sender i's last purchase and the day of the experiment. We are interested in the moderator effect of the variable -- how the effect of a call for a referral campaign on senders' referral behavior changes over time after the purchase. As the timing of the experiment was exogenous to the recency of senders' last purchase, the coefficient of $WeeksSinceLastPurchase_i$ variable captures this dynamic effect. Despite the anecdotal evidence indicating that user's response to the referral campaign changes over time, this dynamic property of response to referral program has received less attention in the prior research. Lastly, we also control for sender's behavior prior to the experiment, including purchase characteristics such as number of past purchases (e.g. $NumPurchase_i$), amount of money paid (e.g. $Spending_i$), discount received (e.g. $Discount_i$), and daily deal channel used (e.g. $DailydealPurchase_i$) across different product categories k (e.g. Blanket, Photobook, Canvas, and others).

To further test how different customer characteristics moderate the effect of call for sharing, we interact the moderating variables with the test group indicator and estimate the model using the following specification

$$Y_i = \alpha + \beta_1 \times Treatment\_egoistic_i + \beta_2 \times Treatment\_equitable_i + \beta_3 \times Treatment\_altruistic_i + \beta_{Moderator\_egoistic} \times Treatment\_egoistic_i \times Moderating\_var_i + \beta_{Moderator\_equitable} \times Treatment\_equitable_i \times Moderating\_var_i + \beta_{Moderator\_altruistic} \times Treatment\_atruistic_i \times Moderating\_var_i + \beta \times Control\_var_i + \varepsilon_i \quad (3)$$

where $Moderating\_var_i$ denotes different moderating variables such as sender's past purchase behavior, NPS score, and the recency of sender's last purchase and where $Control\_var_i$ denotes all the control variables used in equation 2.

Results

Before reporting the results of the analysis, we first compare the differences in sender's characteristics across the four test groups to assess whether the randomization has been successful. Table 1 demonstrates that our sample is well balanced across all the covariates, supporting the validity of our randomization procedure.

Table 1: Randomization Check

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

Main results

Table 2 reports the main results of our model specifications for the three outcomes of interest. The results of linear probability model show that, relative to the control group, only the altruistic framing significantly increases the probability of sender making referrals more than 60% compared to the baseline group. (Table 2, column (1)). The effect of altruistic framing is also significantly higher than the effect of egoistic framing (T3-T1) by 113% and equitable framing (T3-T2) by 29%. When looking at the total number of referrals, we find that both equitable and altruistic framing significantly increases the total number of referrals compared to control group by 43% and 86%, respectively. (Table2, column (3)). Again, the effect of altruistic framing on total number of referrals is significantly higher than the effect of egoistic framing (T3-T1) by 43% and equitable framing (T3-T2) by 16%. The results of the total number of referrals conditional on sharing decision show that only egoistic framing is significantly higher than control (T1-C). Altruistic framing is also higher than control but is only weakly significant at 0.10 level. The results indicate that altruism increases a sender's likelihood of sharing, but does not affect the number of shares per sender.

The results in column (5) presents the effect of different calls for sharing on the sharing outcomes. The results show that altruistic framing leads to significantly larger number of recipients' purchases (by 245%) compared to the control group. A comparison between altruistic framing and other framing effects shows that altruistic framing leads to significantly higher number of recipients' purchases compared to both egoistic framing (T3-T1) by 425% and equitable framing (T3-T1) by 135%. All the impacts are statistically significant and economically sizable. In addition, we find that the conversion rate (= total number of success referrals / total number of shares) of altruism group is 85% higher than the control group, 164% and 81% higher than egoism group and equitable group, respectively.

In addition to the main effects, we control for NPS score, the elapsed time since last purchase, and multiple senders' purchase characteristics based on different product types (Column 2, 4, 6). The NPS score has a significantly positive impact on sharing behavior indicating that customers with high NPS score are significantly more likely to respond to the campaign and make referrals. The elapsed time between sender's last purchase and the day of the referral campaign has a significantly negative effect on all the outcome variables indicating that effect of referral campaign on customers' sharing behavior decreases over time after the purchase. As the timing of the experiment was exogenous to the recency of senders' last purchase, the variable captures how the effect of call for sharing campaign on senders' sharing behavior changes over time after the purchase. The result suggests that immediately after customers purchase is the best time for firms to engage customers with call for sharing.

Table 2: Main Effect

DV	Referral decision		Total number of referrals		Number of recipients' purchase	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0060*** (0.0009)	0.0108*** (0.0016)	0.0083*** (0.0017)	0.0179*** (0.0031)	0.0002 (0.0003)	0.0014*** (0.0005)
T1 (Egoistic)	-0.0015 (0.0010)	-0.0014 (0.0010)	-0.0005 (0.0020)	-0.0004 (0.0020)	-0.0001 (0.0003)	-0.0002 (0.0003)
T2 (Equitable)	0.0014 (0.0010)	0.0015 (0.0010)	0.0036* (0.0020)	0.0037* (0.0020)	0.0001 (0.0003)	0.0000 (0.0003)
T3 (Altruistic)	0.0036*** (0.0010)	0.0036*** (0.0010)	0.0071*** (0.0020)	0.0072*** (0.0020)	0.0005* (0.0003)	0.0005* (0.0003)
Survey	-	-0.0019 (0.0030)	-	-0.0061 (0.0060)	-	-0.0003 (0.0009)
NPS	-	0.0011*** (0.0003)	-	0.0022*** (0.0006)	-	0.0001 (0.0001)
WeeksSinceLastPurchase	-	-0.0012*** (0.0001)	-	-0.0022*** (0.0002)	-	-0.0002*** (0.0000)
NumPurchase_Blanket	-	0.0030*** (0.0008)	-	0.0084* (0.0015)	-	1.28E-05 (0.0002)
Spending_Blanket	-	3.32E-06 (0.0000)	-	1.47E-05 (0.0000)	-	8.22E-07 (0.0000)
Discount_Blanket	-	0.0071*** (0.0016)	-	0.0056* (0.0033)	-	0.0012** (0.0005)
DailydealPurchase_ Blanket	-	-0.0018*** (0.0006)	-	-0.0031*** (0.0011)	-	-0.0004** (0.0002)
NumPurchase_ Photobook	-	0.0104*** (0.0019)	-	0.0159*** (0.0037)	-	0.0016*** (0.0006)
Spending_Photobook	-	-0.0001** (0.0000)	-	-0.0001** (0.0000)	-	-1.3E-05* (0.0000)
Discount_Photobook	-	0.0036 (0.0026)	-	0.0084 (0.0053)	-	0.0004 (0.0008)
DailydealPurchase_ Photobook	-	-0.0094*** (0.0016)	-	-0.0154*** (0.0032)	-	-0.0015*** (0.0005)
NumPurchase_Canvas	-	0.0016 (0.0016)	-	0.0072** (0.0032)	-	5.11E-05 (0.0005)
Spending_Canvas	-	-5.3E-05*** (0.0000)	-	3.55E-05 (0.0000)	-	9.17E-06** (0.0000)
Discount_Canvas	-	0.0044* (0.0024)	-	0.0022 (0.0049)	-	-0.0002 (0.0008)
DailydealPurchase_ Canvas	-	-0.0024* (0.0013)	-	-0.0070*** (0.0027)	-	-0.0002 (0.0004)
NumPurchase_Others	-	0.0026*** (0.0006)	-	0.0029** (0.0012)	-	0.0009*** (0.0002)
Spending_Others	-	-1.9E-06 (0.0000)	-	2.8E-06 (0.0000)	-	-1.4E-06 (0.0000)
Discount_Others	-	0.0083*** (0.0014)	-	0.0142*** (0.0029)	-	6.4E-05 (0.0004)
DailydealPurchase_ Others	-	-0.0030*** (0.0006)	-	-0.0037*** (0.0012)	-	-0.0007*** (0.0002)
p-value (T3 – T1)	<.0001	<.0001	<.0001	<.0001	0.0028	0.0028
p-value (T3 – T2)	0.0026	0.0029	0.0123	0.0138	0.0338	0.0325

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

In summary, we find that framing the same information differently in call for sharing can systematically affect customers' sharing decision and sharing outcomes The main results of the analysis show that altruistic call for sharing is most effective in driving sharing behavior and result in better sharing outcomes. Specifically, altruistic framing significantly increases not only the likelihood of sender making referrals, but also the total number of successful referrals, and the number of successful referral purchases compared to control group. In addition, the effect of altruistic framing is significantly higher than the effect of egoistic framing and equitable framing for a majority of the sharing outcomes.

The overall results imply that altruistic framing increases sender's likelihood of sharing by enhancing her altruistic feelings. While it could arguably be the case that altruism might decrease the effectiveness of sharing as it becomes harder for senders to identify potential recipients and as this will result in fewer shares, however, the results indicate that altruism significantly increases sharing outcomes by maintaining similar number of shares per sender but increasing the conversion rate relative to the other framing strategies.

Heterogeneity in treatment effect

Our rich archival dataset facilities us to explore heterogeneity in treatment effects as well as uncover the mechanisms that explain the treatment effects. Specifically, we test whether the effect of altruistic framing varies based on customer characteristics and the timing of the call for sharing. If altruism is an important driver of information sharing, we should see the higher impact of altruistic framing for customers with high affinity of the product, as customers will care more about their friend's utility and in this case, customers will project their own preferences onto others (Cronbach, 1955; Ichheiser, 1946). For a similar reason, if altruism is an important driver of online referrals, we should expect the effect of altruistic framing on referral behavior may decrease fast over time as such referral behavior is relying on customers' intrinsic delight/altruism about the product, which may decay over time after their purchase.

Customers with high affinity of the product can be represented by their repeat purchases (Hoyer, 1984) and by their reported NPS score (Reichheld 1996). Therefore, we examine the moderating effects of repeat purchases and NPS score on the treatment effect of different calls for sharing. Using archival data on individual purchase history on the platform, we construct a binary indicator $RepeatPurchases_i$ which indicates whether a sender made more than two purchases in the past, and interact the variable with the treatment group indicator. We report the results in Table 3. We find that the effect of altruistic framing on referral behavior is significantly higher for customers who made repeat purchases. Using the same specification, we examine the moderating effect of NPS score (Table 4) and find that the reported NPS score of a customer positively moderates the effect of altruistic framing on their referral behavior. Customers with a high NPS score are significantly (~73%) more likely to share when they are targeted with an altruistic framing call for sharing. Overall, our results are aligned with the theorizing that altruism plays an important role in driving referrals.

Table 3: Moderating Effects of Repeat Purchases

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

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

Table 4: Moderating Effects of NPS Score

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

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

We further explore the moderating effect of timing. We expect that the effect of altruistic framing on referral behavior may decrease as more time passes between the customers' last purchase and the call for sharing. This would be consistent with decay in enthusiasm or delight after purchasing the product. We present the moderating effect of the recency of customer's purchase in Table 5. We find that the effect of referral campaign on customers' referral behavior decreases over time (the coefficient of "WeeksSinceLastPurchase" is negative). More interestingly, we find that the recency of customers' purchases positively moderates the effect of altruistic framing on the number of referrals. Practically speaking, our analysis suggests that firms should target high affinity customers first in their referral campaigns, and that the best time to initiate call for sharing is immediately after purchase, when customers are most enthusiastic about the product.

Table 5: Moderating Effects of Timing

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

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

Post-experiment survey

The empirical results imply that altruistic framing increases sender's likelihood of sharing by enhancing his/her altruistic feelings. In addition, the altruism originated by 'altruistic' framing has a positive effect on sharing outcomes as senders now care more about friend's utility and put more effort on finding the potential recipients which results in higher conversion rate. Although we find consistent and supportive evidence while exploring the heterogeneity in treatment effect, these results based on observational data alone are not enough to make a clear inference of underlying motives that drives sharing behavior and outcomes.

Therefore, we conduct a post-experiment survey with the customers in the experiment to gain a deeper understanding of the motives that explain consumers' sharing behavior and outcomes. After 3 weeks of the experiment, we designed and distributed one separate multiple choice question to customers who shared and didn't share and asked them to choose the motives to share and not to share. Figure 3 describes two questions and choices sent to each customer. We had three specific objectives in conducting this post-experiment survey: (1) to validate whether the manipulation in our experiment design had its intended effect; (2) to measure the impact of different framing on customers' motives to share and not to share; and (3) to understand how these different motives connects to customers' sharing decision and outcomes.

Survey to non-sharer

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

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

Survey to sharer

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

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

Figure 3. Questionnaire in the Survey

Out of nine choices in the question, we find that customers report significantly differently across treatment group in four choices. Figure 4 and 5 depict the mean and the standard errors of the four choices in the question. Significantly different motives across groups may explain the different sharing behavior and outcomes across groups. The left-panel in Figure 4 presents response to the question: "I feel guilty or uneasy about using referral incentive programs". Compared to control group and egoistic group, we find that significantly less number of customers in the altruistic groups report that the guilt feeling was the reason they didn't share. The results show that altruistic framing reduces sender's guilt feeling from getting referral rewards.

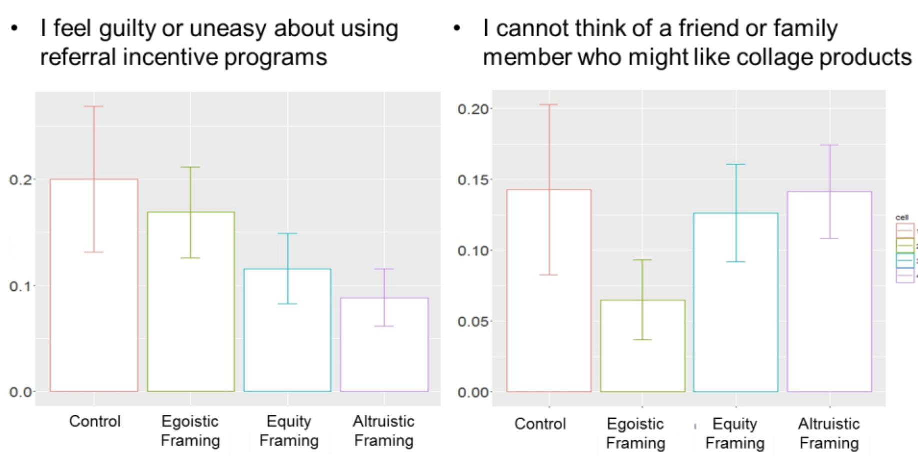

Figure 4. Response of Motives Not to Share

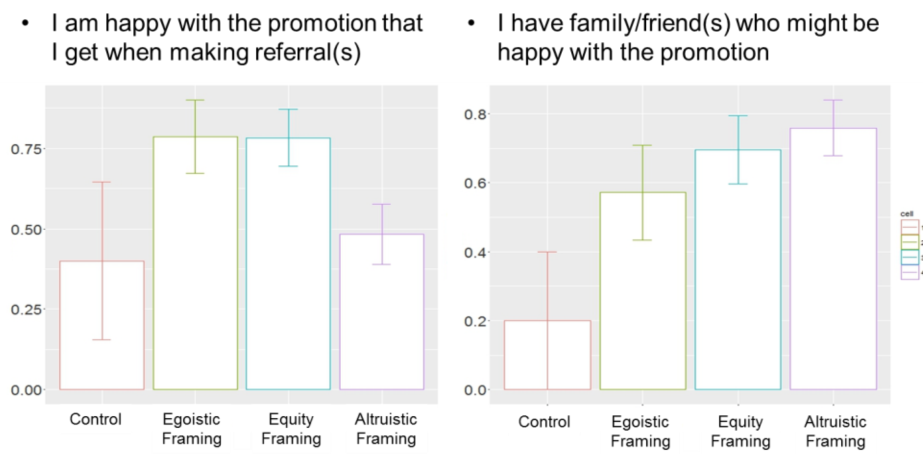

Figure 5. Responses of Motives to Share

The right-panel in Figure 4 presents response to the question: "I cannot think of a friend or family member who might like collage products". The figure indicates that altruistic framing doesn't decrease the difficulty for the sender to identify a potential recipient compared to control group, as altruistic framing affects sender to care more about recipient's utility when making a share. However, the results from our analysis show that this tension doesn't negatively affect the probability to share or the total number of shares. On the contrary, altruistic framing was most effective in driving sharing behavior and sharing outcomes. The results from the survey together with our empirical findings suggest that guilt feelings may be the main motives for customers not to share. Therefore, when designing the referral program, reducing the feeling of guilt of customers is important to increase the effectiveness of the share.

The left-panel in Figure 5 presents response to the question: "I am happy with the promotion (70% discount) that I get when making referral(s)". The figure shows that compared to customers in control group and altruism group, more customers in egoistic group and equitable group shared because of reward to themselves. The right-panel in Figure 5 presents response to the question: "I have family/friend(s) who might be happy with the promotion (70% discount)". The figure shows that significantly larger number of senders in altruistic group made a referral because of altruism compared to control group. The two panels in Figure 5 show that different ways of framing messages impact different motives of senders to share and customers who share because of specific motive (e.g. altruism) are more likely to respond to the corresponding framing (e.g. emphasizing altruism). In addition, the results provide evidence that increasing their friends' utility is the main reason that result in highest conversion rate of altruism group.

Overall, the survey fulfilled all objectives listed above. First, a significant difference of customers' motive consistent with our manipulation confirms that the manipulation was successful. Second, survey results align nicely to explain the impact of different framing effect on different customers' motives. The results show that altruistic framing reduces senders' guilt and enhances altruism, whereas egoistic framing enhances egoism but doesn't reduce guilt. Finally, the results show how altruistic framing positively affects both sharing decision and outcomes through different mechanisms. On the one hand, altruistic framing increases sender's probability to share by reducing his/her guilt from getting referral rewards. On the other hand, altruistic framing improves sharing outcome by enhancing the altruistic feeling and encouraging selective sharing behavior.

Conclusions

Firms increasingly rely on digital word-of-mouth to increase their customer base and product sales. Given the existing knowledge on the effect of incentive design and message design, it is important to understand the effect of different call-to-action on customers' sharing behavior. In this paper, we design and conduct a randomized field experiment that allows us to examine this question in a causal manner. Our results show that altruistic call for sharing leads to higher likelihood of sharing and better sharing outcomes. Such altruistic framing is most effective for customers with more purchases and higher spending in the past and with higher NPS score. The effect of altruistic framing decays significantly after customer's purchase.

Our study provides direct managerial implications to firms on the optimal design of call for sharing campaigns. Specifically, our results offer concrete guidance on how, to whom and when should firms initiate call for sharing.

Understanding which type of call for sharing is most effective in creating WOM is a crucial step in developing optimal referral marketing strategies. We believe our study complements the rich IS and digital marketing literature on social marketing by providing empirical analysis of different call-to-action for information sharing. Theoretically, our study is also among the first to show that altruism is an important driver of information sharing among customers and how such motive leads to sharing decision and sharing outcomes. In this way, the study also shed light on the motives underlying senders' information sharing. Finally, we have discussed the difference between call for sharing and call for purchase and found the two forms of marketing communication are complementary in timing, audience and motives.

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