Monetizing Sharing Traffic through Incentive Design: Evidence from A Randomized Field Experiment

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Abstract
Despite the large volume of information sharing across digital platforms, no study has systematically investigated how firms can monetize such sharing traffic. Our study examines whether and how firms can engage customers involved in online sharing, through the design of novel incentive mechanisms. We design and implement a large-scale randomized field experiment to test the effectiveness of different incentive designs in converting customers in the share. We find evidence that incentive design has a significant impact on both sender's purchase and referrals, but in a different ways. Specifically, compared to the senders who receives non-shareable promotional code, senders who receives shareable code are less likely to make purchase themselves, but much more likely to make further referrals. We further leverage exogenous variation in incentive design to untangle three motives underlying the sender’s sharing -- 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). We find evidence that the effect of incentive designs critically depends on the motive underlying the sender’s sharing. We discuss how firms can customize incentive design at individual level based on such sharing motive. Our findings not only provide practical implications for firms to monetize sharing traffic, but also shed light on theoretical underpinnings of sharing.

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2 The bulk of this study is done by a doctoral student (Tianshu Sun).
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. 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. Our 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 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

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3 In our 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.
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. We conduct 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, our 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 our 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, we 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, we 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). We focus on two dimensions in our incentive design – the number of promo codes available to the sender and whether these promo codes can be shared. By varying the two dimensions, we 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), we 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.

We choose participants in our experiment to be senders who had shared deals with friends the previous day but did not purchase themselves. We 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 us 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. We find evidence that the incentive
structure has a significant impact on both purchase and referral decisions of the sender, but in different ways. Specifically, we 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. We 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. We 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. We 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. Our 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. We 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 our 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 our 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. Our 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 proposed 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. Our 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. Our 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 our 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. We indeed see evidence of such a tradeoff in our results. In summary, our study is among the first to study how firms could distinguish between different sharing motives and customize the design of targeting strategies accordingly.

Related Literature

Our study is closely related three streams of research: first, our 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. We study a novel type of behavioral targeting based on sharing behavior.

Our 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’, we 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. Our 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, our study proposes a new type of network intervention to inject social influence into the network.

Finally, our 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. Our field experiment helps address the endogeneity problems and provides additional insights.
Research Context

In collaboration with a leading online daily-deal platform, we 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.

Experiment Design

Our experiment focuses on senders who had shared deals with friends the previous day but did not end up purchasing the shared deal themselves\(^5\). We 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, we 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

\(^5\) We choose one day as the time lag after based on historical data. Most senders purchase the deal within few hours.
Treatment 2 (T2): Email with one 15% promo-code for the sender to purchase the shared deal

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, we seek to identify the impact of incentive design on sender’s purchase as well as referral behaviors. Specifically, we 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.

Data

The randomized field experiment has been run on the platform for a period of time and we are 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 our study comes from customer-to-customer shares/referrals through the platform. For every firm-mediated email share, we 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. We 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. We 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 us to analyze the impact of incentive design at a granular level (i.e. heterogeneous treatment effect or moderating effect of sender and product characteristics).

**Empirical Results**

We first check the validity of our randomization. In table 1 we 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 our randomization works.

We 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, we 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. We present the detailed results of our field experiment in the following sections.
The Effect of Incentive Design at Aggregate Level

We 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: We 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, we 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, we further look into our data to untangle the motives underlying sender’s sharing. We first report two heterogeneities in the treatment effect, based on the sender’s purchase history as well as the recipient’s purchase history. Specifically, we construct a continuous variable capturing the ‘alignment’ between the shared deal and the customer’s revealed preference. We do it in two steps: first, we 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, we 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). We 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.

We 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 our sample range across more than 40 subcategories. We 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 our hypotheses that group regarding preference dominates customers’ sharing of social products.

*Customizing Incentive Design Based on the Sharing Motives of the Sender*

Our 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.

Conclusion

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. Our 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. We 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. Our work serves as a valuable proof-of-concept of this impending development.

In conclusion, our study represents one of the first large-scale field experiments to understand the causal role of incentive design on converting customers in sharing traffic. Our study not only contributes to our understanding of the motives behind online sharing, but our 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. We hope that our study serves as a first step in that direction.
References

Appendix: Figures and Tables

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

<table>
<thead>
<tr>
<th>Test Group</th>
<th>Sample size</th>
<th>Number of past purchase</th>
<th>Total past spending</th>
<th>Days after creating account</th>
<th>% of share through Facebook</th>
<th>Deal Price</th>
<th>Deal Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>4309</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00%</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>4045</td>
<td>-0.12</td>
<td>-6.01</td>
<td>6.08</td>
<td>-1.32%</td>
<td>4.14</td>
<td></td>
</tr>
<tr>
<td>T2</td>
<td>4050</td>
<td>0.14</td>
<td>-0.16</td>
<td>-14.09</td>
<td>0.96%</td>
<td>-1.51</td>
<td></td>
</tr>
<tr>
<td>T3</td>
<td>4007</td>
<td>-0.16</td>
<td>1.86</td>
<td>4.19</td>
<td>-1.36%</td>
<td>-2.29</td>
<td></td>
</tr>
<tr>
<td>T4</td>
<td>4069</td>
<td>0.17</td>
<td>0.52</td>
<td>-0.09</td>
<td>1.25%</td>
<td>3.52</td>
<td></td>
</tr>
</tbody>
</table>

p value for joint test (C=T1=T2=T3=T4=T5) | 0.82 | 0.99 | 0.44 | 0.33 | 0.34 | 0.34 |

* 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

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Sender’s Purchase</th>
<th></th>
<th>Sender’s Referral</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percentage lift in sender’s purchase</td>
<td>p-value</td>
<td>Percentage lift in sender’s referral</td>
<td>p-value</td>
</tr>
<tr>
<td>Effect of Reminder on Sender’s Purchase or Referrals (T1-C)/C</td>
<td>14.1%</td>
<td>0.198</td>
<td>7.8%</td>
<td>0.598</td>
</tr>
<tr>
<td>Effect of one non-shareable code on Sender's Purchase or Referrals: (T2-C)/C</td>
<td>64.5%</td>
<td>0.000</td>
<td>18.3%</td>
<td>0.286</td>
</tr>
<tr>
<td>Effect of one shareable code on Sender's Purchase or Referrals: (T3-C)/C</td>
<td>31.6%</td>
<td>0.002</td>
<td>67.4%</td>
<td>0.005</td>
</tr>
<tr>
<td>Effect of two codes on Sender's Purchase or Referrals: (T4-C)/C</td>
<td>27.8%</td>
<td>0.007</td>
<td>29.5%</td>
<td>0.125</td>
</tr>
</tbody>
</table>
Table 3: Other-regarding preference
Main Effect of each treatment on sender’s referral behavior

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>Total Referrals</th>
<th>Sender only makes referral (without purchase)</th>
<th>Sender makes both referral and purchase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percentage lift in average number of referrals from each sender</td>
<td>p-value</td>
<td>Percentage lift in average number of referral from each sender</td>
</tr>
<tr>
<td>Effect of Reminder on Sender's referral (T1-C)/C</td>
<td>7.8%</td>
<td>0.598</td>
<td>9.60%</td>
</tr>
<tr>
<td>Effect of one non-shareable code on Sender's Referral: (T2-C)/C</td>
<td>18.3%</td>
<td>0.286</td>
<td>17.4%</td>
</tr>
<tr>
<td>Effect of one shareable code on Sender's Referrals: (T3-C)/C</td>
<td>67.4%</td>
<td>0.005</td>
<td>92.5%</td>
</tr>
<tr>
<td>Effect of two codes on Sender's Referrals: (T4-C)/C</td>
<td>29.5%</td>
<td>0.125</td>
<td>11.3%</td>
</tr>
</tbody>
</table>
Table 4: Group-regarding preference
Main Effect of each treatment on the Co-Purchase decision with friends (sender makes both purchase and referrals)

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>All products</th>
<th>Social product</th>
<th>Standalone product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage lift in the number of senders who makes both purchase and referrals</td>
<td>p-value</td>
<td>Percentage lift in the number of senders who makes both purchase and referrals</td>
<td>p-value</td>
</tr>
<tr>
<td>Effect of Reminder on Co-Purchase (T1-C)/C</td>
<td>-4.7%</td>
<td>0.840</td>
<td>-25.7%</td>
</tr>
<tr>
<td>Effect of one non-shareable code on Co-Purchase: (T2-C)/C</td>
<td>20.5%</td>
<td>0.388</td>
<td>42.7%</td>
</tr>
<tr>
<td>Effect of one shareable code on Co-Purchase: (T3-C)/C</td>
<td>26.2%</td>
<td>0.283</td>
<td>45.1%</td>
</tr>
<tr>
<td>Effect of two codes on Co-Purchase: (T4-C)/C</td>
<td>47.1%</td>
<td>0.116</td>
<td>103.2%</td>
</tr>
</tbody>
</table>
## Table 5: Heterogeneity in treatment effect
Based on the sender’s and the recipient’s revealed preference on the shared deal

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Sender’s Preference on the shared deal</th>
<th>Recipient’s Preference on the shared deal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variables</td>
<td>Sender’s Purchase</td>
<td>Sender’s Referral</td>
</tr>
<tr>
<td>Effect of one non-shareable code on Sender’s Purchase: (T2-C)/C</td>
<td>0.002</td>
<td>-0.043**</td>
</tr>
<tr>
<td>Effect of one shareable code on Sender’s Purchase: (T3-C)/C</td>
<td>0.026*</td>
<td>-0.032*</td>
</tr>
<tr>
<td>Sample size</td>
<td>20,375</td>
<td>20,375</td>
</tr>
</tbody>
</table>