Referral Reward Programs and Customer Acquisition *

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Referral reward programs are widely recognized as a cost-effective strategy for customer acquisition, leveraging the power of word-of-mouth and user incentives. However, key elements such as incentive size, recipient identity, and their influence on the composition of new customers are crucial for understanding the effectiveness of these programs and remain largely unexplored in empirical research. We evaluate the impact of a referral reward program on customer acquisition for a fintech banking platform in Mexico. Through a series of consecutive experimental interventions, we find that referral incentives significantly boost referral likelihood by a factor of 2, with users responding twice as strongly to rewards for themselves than their referred peers. However, previously incentivized users demonstrate a third of the propensity to make further referrals, although previous referrers (i.e., compliers) have a higher likelihood to further refer and should then be targeted by the firm. Additionally, referred users from incentivized customers show lower app engagement during their first year. These findings indicate diminishing returns for referral marketing, how incentive design and targeting matter, and suggest a potential trade-off between customer acquisition and user quality.

Key words: customer acquisition, referral rewards, targeted marketing, incentives design

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1 Introduction

Managers face the fundamental problem of how to grow their customer base at the lowest possible cost. Customer acquisition is crucial for generating revenue, particularly for firms where marginal costs are low and repeated interactions are a cornerstone of the business model, such as software-as-a-service companies. Moreover, higher customer growth can also enhance the firm's reputation, brand building, and ability to secure capital from investors. However, the quality of new customers—specifically, their fit with the product and their contribution to profitability—is essential for realizing these returns.

One particular approach regularly implemented by firms are customer referral reward programs, in which existing users are offered a monetary or in-kind incentive to persuade their friends to sign up for the company's service. This marketing strategy aims to magnify word-of-mouth growth. Because the firm only pays for each acquired customer, these programs are considered cost-effective, due to the low reward amounts and the predictability of the return on investment (Edinger, 2021; Helm, 2003). Furthermore, it is often argued that these referred users are profitable because of homophily (Viswanathan et al., 2018; Van den Bulte et al., 2018), because satisfied customers are more likely to refer others (Biyalogorsky et al., 2001), and because existing customers may be better able to identify non-users, among their group of peers, who are a good fit for the firm's product (Kornish and Li, 2010).

Systematic information on the share of firms that engage in incentivized referral marketing is (to our knowledge) not readily available, but, anecdotally, many companies offer their users some type of reward if they refer a friend (for instance, Dropbox, Uber, and American Express, to name a few). Specifics of these programs, including the type of reward (e.g., money, gift cards, discounts) and who gets rewarded (i.e., the person making the referral, the new user, or both), vary across companies. In a small survey of firms in the US with referral programs, more than half of them provide monetary incentives, more than 90% are double-sided, and among those programs about 72% of them provide balanced rewards, meaning that both the existing and new user are incentivized with the same amount (SaaSquatch, 2020).

In this paper, we ask how the likelihood of making a referral changes with the reward amount, with the identity of who receives the reward, and with previous exposure to the reward program.

Furthermore, we analyze differences in the characteristics and activity of the referred users. To answer these questions, we partnered with a financial technology platform in Mexico that operates exclusively as a mobile application, offering its customers credit and a checking account.

The firm implemented a series of randomized interventions from September to December 2021 to bolster their customer growth via referrals. They carried out two sets of experiments each month for different customer segments based on their historical engagement with the product: those that had made at least one purchase recently (high engagement) and those that had only made some other type of transaction recently (low engagement). Each treatment arm within an experiment consisted in different reward amounts offered to the person making the referral and to the referred user, with mostly double-sided (i.e., both existing and new users received an incentive) and unbalanced (i.e., larger amounts for the referrer) rewards. For existing users making referrals, these amounts range from 100 to 400 Mexican pesos ($4.86 - 19.45$ USD), and for the new customers signing up between 0 and 200 pesos ($0 - 9.72$ USD).[1] To contextualize, the daily minimum wage in Mexico during this period was 142 pesos (6.90 USD). Moreover, in our data, the average value of purchases logged by app users was 734 pesos per month. The control groups were not incentivized monetarily.

Using anonymized account-level data on the experiment participants, we estimate that referral rewards have a significant impact on the likelihood of making at least one referral. Across interventions and types of users (more vs less engaged), we find that, on average, the incentives double the users' referral activity, relative to no incentives. We further show that users are more responsive to amounts that accrue to them instead of their friends, and that the effect of the incentives is increasing in the reward amount, regardless of the identity of the recipient. Here, we also find that the more engaged users of the app are more responsive to increments in the reward amount that they receive than the less engaged users. Given that users were eligible for being involved in multiple interventions over time, we also show that new participants (i.e., existing customers that had not been part of any previous interventions, whether in the control or treatment arms) are much more responsive to the incentives than customers who had already been assigned to an experimental intervention in the preceding months. On the other hand, users who have previously referred someone, are (slightly) more likely to keep referring. This suggests that referral marketing exhibits diminishing returns, but is effective and can be targeted to referrers once they are found.

[1] From September to December 2021, the average exchange rate was 20.57 pesos for one USD.

Next, we examine data on the referred users to demonstrate that those referred by an incentivized customer are, on average, similar to those referred by a non-incentivized customer (i.e., control group customer) in terms of the sociodemographic characteristics we observe. However, in terms of their activity on the app, we find that new users referred by a treated customer have lower engagement on the app, particularly in terms of their transactions and their own probability of making a referral. This may suggest that, at least in this setting, there is a trade-off between referral marketing and customer quality/profitability.

This paper speaks to the marketing literature that has analyzed customer referral programs. Although theoretical models have been formulated (Biyalogorsky et al., 2001; Kornish and Li, 2010), we focus our attention on the empirical studies, given that our contribution is also empirical. Some studies center on the question of how referral activity changes with reward size. Wolters et al. (2020) analyzes a field experiment with active customers of an online bank in Germany and finds that changing the reward from 20 to 50 euros increases the referral probability by a factor of eight, although this amount is nearly twice the reported customer profitability. In lab experiments, Ryu and Feick (2007) finds that monetary incentives increase the referral likelihood by 15 percentage points (relative to no incentive), but no additional effect when the amount is doubled.

Other studies consider additional factors that may matter for the success of referral programs. Belo and Li (2022) uses data from a field experiment in an online dating platform to emphasize a potential trade-off: social referral programs can boost referrals but reduce revenue, with increased referral requirements generating more referrals and revenue but potentially lowering these users' engagement on the platform.[2] Hong et al. (2017) explores how social distance (i.e., how close the relationship is between referrer and referred person) mediates the success of balanced vs unbalanced referral designs, finding that for those with a large social distance, balanced referral programs are more successful.[3] Xu et al. (2023) shows that disclosing to the referred person that the referrer is getting a reward promotes successful referrals, but only if the referrer is not getting more money than their peer. Fernández-Loría et al. (2023) finds that users of a ride-sharing platform generate more and higher-value referrals when they are frequent users of the platform and have gained

[2]The existence of such a trade-off may be context-specific. For instance, Garnefeld et al. (2013) shows that for a global cellular telecommunications company, participating in a referral program increases customer loyalty, as measured by a decline in referrers' defection rates.

[3]Others have emphasized the connectedness of individuals within a network to gauge potential trade-offs between having access to a wider scope of peers and being able to influence or have "power" over them (Hinz et al., 2011).

experience, but their referral activity decreases significantly after making initial referrals due to a diminishing pool of potential friends to refer.

We contribute to this literature in at least five ways. First, in our setting, rewards are modest, ranging from 100 to 400 pesos, or between 14 and 54% of the average monthly value of purchases. Second, we can analyze different quantities, including a no-reward condition, with variation in awards that are one- vs double-sided and balanced vs unbalanced. Third, the sequential nature of the incentives allows us to explore dynamic effects. Fourth, all interventions are randomized, allowing us to identify *causal* effects from these variations in program design. Fifth, we can distinguish between current customers that are more vs less engaged with the app, as measured by their activity in the preceding months.

Other studies have also centered on the issue of the identity of the recipient of the reward. Ryu and Feick (2007) finds that for weak brands it is more important to reward the person making the referral, while for stronger brands rewarding the referred person also matters. Jin and Huang (2014) further shows that in a lab experiment monetary incentives (instead of in-kind gifts) are more effective at increasing referrals when compensation is double-sided (relative to just rewarding the referrer). In addition, Wang and Chen (2022) emphasizes the role of social connectedness between the referrer and referred person for determining whether rewarding one or the other yields larger effects. We contribute to this literature by exploiting variation in the reward amounts for both the user making the referral and the person being referred, including a no-money condition for the latter.

Finally, some papers focus instead on the quality or profitability of the referred users. Wolters et al. (2020) shows that while a larger reward leads to more referrals, these new users are less profitable for the company. In contrast, analyzing a field experiment—also at a German bank—Schmitt et al. (2011) finds that customers referred by incentivized users are actually more valuable than those that signed up organically. Although the higher contribution margin of these referred customers is short-lived, their higher retention rate persists over time. In the context of an online dating platform, Belo and Li (2022) obtains that the average quality of referred users is unaffected by variations in program design. We add to this long-standing discussion by analyzing the characteristics and behavior of customers that were referred by incentivized and non-incentivized users in our setting.

2 Background

In Mexico, a large segment of the population remains unbanked, as evidenced by the 2021 wave of the National Survey on Financial Inclusion (ENIF, 2021). These data reveal that only 49% of the adult population aged 18 to 70 reported having an account, for savings and payment transactions, at a formal financial institution. Strikingly, only one-third of this cohort indicated access to formal credit facilities. Conversely, 77% of the adult population had access to smartphones, according to the 2020 wave of the National Survey on Availability and Use of Information Technologies (ENDUTIH, 2020).

Within this context, our partner firm is a financial technology (fintech) platform that has been operating in Mexico for a few years. This company is characterized by its lack of physical locations, operating exclusively as a mobile application. Through this fintech app, the firm offers a range of credit options and a checking account (i.e., debit account) that facilitates costless transfers and deposits both within the platform and with other financial institutions (e.g., banks). Notably, the account opening process only requires the potential user to download the app and submit a copy of a valid government identification. As of 2021, the platform registered a few million users.[4]

As is customary in this fintech setting (Deloitte, 2020), our partner firm predominantly caters to a younger, digitally-savvy clientele who may lack the requisite documentation to open an account at a conventional bank. This situation may be more prevalent among young adults and those working in the informal economy. Moreover, given this "software-as-a-service" business model, which hinges on recurring revenue from established clients (Cespedes and van der Kooij, 2023), the firm prioritizes customer acquisition and expansion. Indeed, acquiring a new customer represents additional revenue through subsequent transactions, while the marginal cost of rendering services is mostly negligible.

The firm has historically employed diverse methodologies for customer acquisition, including digital marketing campaigns and collaborations with affiliates (i.e., individuals or firms that promote the company's products). However, one particularly prominent channel is customer referrals. By allowing users to refer their acquaintances via unique referral codes assigned upon opening their account, the company incentivizes these referrals by providing monetary rewards credited to the

[4] Our nondisclosure agreement prohibits us from providing further specific details regarding this firm.

user's account for each successful referral. The rationale underlying this approach is that the acquisition cost associated with referrals is substantially lower than that of conventional marketing campaigns and, conceivably, yields a more discerning selection of new customers through word of mouth.

To assess the impact of these referral incentives, the firm designed and implemented a series of experimental interventions from September to December 2021. We were not part of this process and only came in contact with the firm until 2022. These interventions were distinct for each of the four months, and each lasted for 28 days. Random variation in the monetary incentive provided to both referrers (i.e., the person making the referral) and referred individuals allows us to estimate the corresponding elasticities. Note that we employ the term "intervention" to collectively denote treatment and control groups within a specific user type.

At the beginning of each month, the experimental design unfolded in two stages. First, users were stratified into different eligibility groups based on their recent activity. Users who had made at least one purchase in the last 60 days qualified for what the company termed "high-engagement customer" interventions. Those deemed not high-engagement were eligible for "low-engagement customer" interventions, provided they had incurred in at least one transaction within the past 90 days. Users who failed to meet either condition were deemed ineligible for any experimental intervention (i.e., "non-engagement customers"). This process is described with the help of a flowchart in Figure A1.

Second, within each user type, individuals were randomly assigned to either the control group or treatment group. In certain instances, multiple treatment groups existed for a given month and user type, but each user was only assigned to a single treatment arm for the duration of that month. Throughout the analysis, we denote the incentives as $[w, z]$, where w represents the monetary value in Mexican pesos provided to the referrer (i.e., existing customer) for each referral made, and z represents the amount granted to the referred individual (i.e., new customer). The control group $[0, 0]$ received no monetary incentive. Irrespective of assignment to treatment or control, all participants received four emails, four push notifications, and four SMS messages encouraging them to refer their friends. In addition, the treatment groups were informed of the monetary incentives.[5,6]

Figure 1 displays the incentives by user type for each month, spanning September to December, along with the sample size of users assigned to each group. These experimental interventions are the focus of our analysis. However, it should be noted that, aside from the groups corresponding to high- and low-engagement users, the firm identified a third user type during September, November, and December, subject to a separate monetary intervention. These users were drawn from the set of ineligible individuals (i.e., neither high- nor low-engagement) who had an outstanding balance on their credit and were not delinquent. Importantly, all users in this category were assigned to a treatment group (i.e., a positive monetary incentive), making it infeasible to establish a valid comparison group. Note as well that, based on the firm's priors, a very large percentage of users were assigned to treatment arms, with the share assigned to the control group becoming even smaller over time (e.g., for the high-engagement types, 10% were assigned to the control in September, but only 2% in December). While we are not underpowered to detect effects in the cross-sectional analysis of the experiments, we have less power to feasibly explore differential effects by prior assignments. We discuss this in depth below, including potential bias from the sequential nature of treatments.

3 Data

We obtained anonymized account-level data aggregated on a monthly basis, consisting of four key components. First, we procured a roster of accounts, capturing time-invariant attributes, like gender, age, occupation, and the account opening date. As noted below, these characteristics are missing for some of the newer users that signed up during the intervention period. Second, we obtained an unbalanced panel of 520,593 customers spanning from January 2021 to January 2022,

[5] The text in these communications read: "Hello [user]! Invite your friends to be part of [company name]. You just have to send them your referral code through the app, and that's it! Once they activate their card, your friends will be part of the [company name] community." For participants in the control group, the header before this text was simply "Invite your friends to [company name]!". For those in the treatment groups where the referred person was not incentivized, it read "Earn [w] pesos for every friend that joins [company name]!" Lastly, whenever both referrer and referred received a reward, the text was "Earn [w] pesos for every friend that joins [company name] and your friend earns [z] pesos!"

[6] Users participating in the low-engagement type interventions received emails and push notifications, though they did not receive SMS messages. However, because treatment and control groups received the same set of communications, we ignore this difference between the low- and high-engagement interventions.

with individuals who participated in any type of intervention during September through December 2021. This includes users that were part of the non-engagement customer interventions, which we do not consider in our analysis. For all users, we observe their referrals, transaction count, purchase count, and the value of their purchases, since their initial registration with the app. Third, we procured an unbalanced panel of 218,361 users who were referred by others. For these referred individuals, observations extend from their signup date until September 2022, with information on their transaction count, purchase count, and the number of referrals they themselves initiated. We do not observe the value of their purchases. Lastly, we obtained a mapping of the referral relationships, specifying the referrer-referred connections.

As indicated above, the customer population at this firm predominantly consists of young adults, with an average age of approximately 33 years. Moreover, slightly over one-third of users identify as female. Around 55% of users reported being employees at the time of signup, while nearly a third indicated self-employment or business ownership. A smaller fraction, below 10%, identified as students, and the remaining users either reported being retired, unemployed, or otherwise occupied.

In our primary analyses, our focus centers on two distinct datasets. To assess the effects of the experimental interventions, we consider the set of users who participated in any high- or low-engagement type intervention during any month. This constitutes a total of 390,035 users. We construct a panel for this group from September to December 2021. This panel is not balanced, as certain users joined during this period (69% of users are observed for the entire four-month duration, having signed up prior to the interventions).

Additionally, we analyze the behavior of users referred through these experiments. We consider the set of customers who were referred by any participant in both types of interventions, including treatment and control groups. This subset comprises a total of 54,164 users. The observation period spans from the month in which the user signed up (September through December 2021) until at most September 2022. For around a third of these users, we do not observe their time-invariant sociodemographic characteristics.

In light of the experimental nature of the interventions, we conduct a series of balance tests across the various groups to ensure the comparability of treatment and control cohorts. Since each user type and month features its own control group, we assess the average differences between each treatment group and its respective control within a given user type and month. Our balance test results are presented graphically in Figure 2, with the top panel displaying the balance tests for high-engagement customers, and the bottom panel depicting those for low-engagement types. Each vertical line is centered at zero, with markers representing the average difference between the treatment group and its corresponding control, while the bars denote 95% confidence intervals around this difference. We assess multiple variables, including time-invariant sociodemographic characteristics (gender, user age at signup, account age in months, and occupation), utilization (number of transactions and purchases in the previous month, and log value of purchases in the previous month), and intervention participation indicators (whether the user participated in a high- or low-engagement intervention in the preceding month and the total number of interventions in which the user participated up until the previous month). Given the definition of low-engagement users, we exclude from this analysis the number of purchases and log purchase value.

The results of our balance tests consistently indicate very minimal differences across all groups, with the majority of these differences statistically indistinguishable from zero. This finding suggests that the randomization process was successful, ensuring that the treatment and control groups share similar characteristics and differ only in terms of the offered monetary incentives. Detailed descriptive statistics of these variables for high- and low-engagement customers are provided in appendix Tables A1 to A4 and Tables A5 to A8, respectively. These tables present the averages and standard deviations for each treatment and control group, offering further support for the comparability of the groups.

4 The Effect of Incentives on Referral Probabilities

4.1 Raw Means

We start by showing the raw differences between treatment and control groups. Recall that the relevant control group for a given incentive $[w, z]$ is the set of users assigned to the $[0, 0]$ incentive (i.e., no money awarded for making a referral to either the referrer or the referred person) in the same month and the same user type. Given that very few users make referrals and that even fewer make more than one referral in a given month, our outcome of interest is whether the customer made at least one referral during the intervention period.

Figure 3 plots the means and standard errors for each group. The top panel shows high-engagement customers, while the bottom panel shows low-engagement types. Across all interventions, there is a clear difference between the control group and treated groups, with the former showing a lower probability of making at least one referral during the intervention period. However, the size of this difference seems to vary by month and user type. We also observe some differences across treatment groups within a given month and user type, with seemingly larger effects for customers assigned to higher monetary awards.

4.2 Empirical Strategy

We now formalize the previous comparison of means across groups by estimating the following ordinary least squares (OLS) equation for high- and low-engagement customers separately:

$$Y_{it} = \sum_{k \in \mathcal{K}} \beta_k \text{Incentive}_{it}^{k=\{[w,z],t\}} + \theta_t + \varepsilon_{it} \tag{1}$$

where Y_{it} describes the outcome of interest for customer i in month t, $\text{Incentive}_{it}^{k=\{[w,z],t\}}$ is an indicator for whether customer i was assigned to treatment k characterized as an incentive $[w, z]$ during month t, $\mathcal{K}$ denotes the set of all intervention groups as depicted in Figure 1, θ_t are month fixed effects, and ε_{it} represents the idiosyncratic error term. We calculate heteroskedasticity robust standard errors.

As noted above, our main outcome of interest is an indicator for whether the customer made at least one referral during the intervention month. We examine other outcomes in the online appendix and discuss them below. The inclusion of month fixed effects guarantees that our comparisons between treatments and control are only within each experiment, and we allow for separate estimates for the same monetary incentives implemented in different months (e.g., for high-engagement users, the $[300, 100]$ incentive was assigned in September and November and we obtain separate average treatment effects for each). The coefficients of interest are denoted by β_k, as they represent the marginal effect of the monetary award relative to not receiving any incentive. As a robustness check, we include customer characteristics as controls, estimate the equivalent Logit specification, and consider the number of referrals made as the outcome variable in a Poisson specification. All yield very similar results.

Given the experimental nature of the interventions and the balance tests in Figure 2, each β_k denotes the causal impact of providing the corresponding monetary incentive $[w, z]$ in month t. The only concern for identification in our setting is the fact that the firm implemented panel experiments, with users sequentially assigned to random interventions over this four-month period. As such, many users are characterized by an assignment path where they participated in different treatments and/or control groups sequentially (for instance, in December, less than 20% of the high-engagement users were participating for the first time; see appendix Figure A2). In this context, conventional OLS estimators will be biased if there is serial correlation in treatment assignments or there are dynamic effects (Bojinov et al., 2021).

Appendix Figure A3 shows that prior assignment to a treatment arm does not differentially change the probability of being assigned to a positive monetary incentive in the current month. This helps validate the random assignment of users in the cross-section. However, and mostly by definition, being a high- or low-engagement type this month means it is more likely that that person will continue being eligible for the interventions next month (i.e., eligibility is likely serially correlated, because it is conditional on past behavior).

The second potential source of bias comes from dynamic effects. The estimated average treatment effect of an incentive is essentially a weighted average of the treatment effects for all possible assignment paths (Bojinov et al., 2021). For instance, for the high-engagement types, the estimated effect of the $[200, 0]$ incentive in October is a weighted average of the effects for users that were assigned to the $[200, 0]$, $[300, 0]$, $[300, 100]$, and $[0, 0]$ groups in September plus the effect for those that had been ineligible in September. Muralidharan et al. (2023) shows that estimating a fully saturated "long" model—by including indicators for all possible assignment groups in the previous month plus the full interactions of current assignments with last month's assignments—allows for correct inference. We show these specifications as a robustness check in the appendix. Moreover, we explore heterogenous effects by whether the user has participated before or not.

4.3 Results

We show results from the linear probability model described in equation 1 in Figure 4. The top panel shows high-engagement customers, and the bottom panel is for low-engagement users. Bars denote the coefficient estimates, while capped spikes show 95% confidence intervals from robust standard errors. We estimate positive and significant effects for all treatment groups on the probability of making at least one referral during the intervention period. For high-engagement customers, this effect hovers around 2 percentage points, with a maximum of around 4 percentage points for the $[400, 100]$ intervention in November. Relative to the referral probability in the control group, these effects are large, on average doubling (or more than doubling in some instances) the users' referral activity. The effect size is smaller among low-engagement users, at less than one percentage point. The largest impact here is around 1.3 percentage points for the $[300, 0]$ intervention in September. However, because these customers are by definition engaging less with the app, the control group means are lower than for high-engagement users. In percentage terms, the incentives, on average, also doubled or more than doubled the referral activity relevant to the control.

The results in Figure 4 also allow us to compare across different incentive amounts. For both types of customers, there seems to be, on average, a slight increase in the effect sizes when the referrer receives a larger amount, regardless of the amount that the referred person obtains. The effect also seems to be increasing in the amount that the referred person gets, but only among low-engagement customers. To better understand these differences, we show the average marginal effects (across months) of the different monetary incentives in Figure 5. These estimates correspond to an OLS regression that swaps the incentive indicators in equation 1 for indicators of the different amounts w that the referrer gets and indicators of the different amounts z that go to the referred person.

Figure 5 documents two findings. First, effects are always larger when the incentive is given to the referrer instead of the referred person. This suggests that the identity of the person receiving the transfer matters and that private transfers of the award between referrer-referred are not common. Second, the effect of the incentives is indeed increasing in both the amount awarded to the referrer and to the referred person. For high-engagement users, doubling the amount that the referrer obtains leads to a treatment effect that is, on average, around twice as large. For low-engagement types, triplicating the reward implies a treatment effect that is twice as large. This also holds for the amount awarded to the referred person, although we only have variation in high-engagement customers to assess this relationship: doubling the reward doubles the treatment effect.

An outstanding question with respect to the results shown in Figure 4 is the fact that in some cases, the same incentive in different months led to significantly different effect sizes on the probability of making at least one referral. For high-engagement customers, three different incentive schemes were implemented in two separate months. While effect sizes were very similar for interventions $[200, 0]$ and $[300, 100]$, there is a stark difference in the estimates for $[400, 100]$ implemented in November versus December. For low-engagement users, only the $[300, 0]$ intervention was repeated in multiple months, again yielding different estimates. In both cases, we obtain smaller magnitudes for the interventions that occurred in later months. As discussed above, we explore one potential explanation below related to the fact that customers were exposed to multiple interventions over time.

4.4 Robustness Checks and Additional Findings

We present a series of robustness checks and additional findings in the appendix. Figure A4 shows estimates from a linear probability model that includes customer characteristics as controls. Unsurprisingly, we find very similar results. Given that referral activity is a low-probability event, one might be concerned about our choice of a linear probability model. To assuage these concerns, Figure A5 shows marginal effects calculated from the equivalent Logit specification. Once more, results are very similar to our OLS estimates. Lastly, one might worry that we are throwing away important variation by dichotomizing users' referral activity. Therefore, we present marginal effects in Figure A6 for the equivalent Poisson specification that uses the number of referrals made by the user as the outcome variable.

Although the firm's main objective with the customer referral reward program is to increase the number of referrals, it is also possible that the users' own activity changes when exposed to these treatments (relative to not getting a monetary incentive). We explore this by estimating the marginal effect of the treatments on the number of transactions, number of purchases, and log of purchase value. Figures A7, A8, and A9 show null effects of the referral incentives on the users' own activity, suggesting that there are no such spillovers.

Lastly, given potential concerns with the sequential assignment into treatment in this panel experiment structure, Table A9 shows estimates of an augmented linear probability model as specified in Muralidharan et al. (2023). Since we do not observe any potential variation in incentives prior to September, we only estimate these models for October, November, and December. Moreover, given that we are underpowered in this exercise since the control groups are such a small fraction of the total sample size in each cohort, we only include indicators for assignments in the previous month (and the full interactions), and not the complete assignment path since September. We obtain different point estimates than those in our baseline specification. However, with the exception of the $[400, 100]$ treatment in December for high-engagement types, all treatment effects are still positive and statistically significant. For the low-engagement interventions, most estimates lose significance with this approach. Sometimes the magnitudes are smaller, sometimes they are larger. Overall, we interpret this exercise as evidence that our positive impacts for the high-engagement types are robust, and suggestive of potential bias from dynamic effects in the panel experiment structure. This further motivates our exploration below of differential effects by prior participation.

4.5 Heterogeneous Effects by Past Assignments and Behavior

As mentioned before, an important feature of the experimental interventions implemented by the firm is that past participation did not preclude a user from being eligible for future interventions. Indeed, after the first month, the share of participants that were included for the first time (i.e., had not participated in experiments in previous months) declined to around 20% for high-engagement and 25% for low-engagement customers (Figure A2). Therefore, we ask how the effects differ for new participants relative to those that had participated in the past, regardless of their previous assignment (i.e., to any treatment group or the control).

Figure 6 shows these estimates. The darker bars correspond to new participants, and the lighter bars are those that had already participated in previous months. This analysis does not include September, since all participants were new in that first month from our perspective (i.e., we cannot observe any potential variation in incentives prior to September). We find that the effects of the referral reward program are much larger among new participants. For high-engagement customers, effects range between 6 and 8 percentage points among those that are participating for the first time, while the estimates are between 1 and 2 percentage points for those that had been in previous experiments. For the $[400, 100]$ incentive, which had yielded significantly different average effects in November and December (Figure 4), we cannot reject that the effect among new participants is equal in these months, even if the point estimate is smaller in the latter. In contrast, we find a significantly smaller effect size among repeat participants in December. This is consistent with diminishing returns of the referral reward program. For low-engagement users, we also find much larger effects among new participants, although we cannot reject that effects are the same across subsamples in the $[300, 0]$ December intervention. Moreover, for the intervention repeated in November and December, we fail to reject that the estimates are equal for the repeat participants across these two months.

In a related exercise, we now stratify experiment participants by whether they had made any referrals prior to the intervention period. This includes incentivized and non-incentivized referrals. These estimates are shown in Figure 7. The darker bars correspond to customers that had never made referrals, and the lighter bars are those that had made at least one in previous months. We again exclude September from this analysis. We find larger point estimates among the group of users that have already made referrals in the past, although in some instances we cannot reject that effect sizes are similar across subsamples. This relationship may seem puzzling, given that the previous exercise suggested diminishing returns: one might expect that customers who have already made referrals would be less susceptible to incentives, which would be consistent with a model where search costs (i.e., finding another friend to refer) increase with the number of previous referrals.

An alternative explanation revolves around composition effects. Indeed, users who had previously made referrals are different from those who had not (for instance, they might be more active on the app or possess a stronger network of friends). We might have two types of users: connected and isolated, which can be thought of as compliers and never-takers. Therefore, we interpret this result as evidence that the endogenous selection into making past referrals seems to overpower the diminishing returns documented in Figure 6. From a managerial perspective, a referral reward program incentivizes compliers, which the firm should further target. But, after the initial wave of incentives, as the firm identifies never-takers, managers may consider to not target them again.

5 Characteristics and Behavior of Referred Individuals

5.1 Effect of Incentives on the Average Characteristics of Referred Users

We begin our analysis of referred individuals by inspecting potential differences in their reported sociodemographic characteristics between those that were referred by non-incentivized (control) and by incentivized customers (treated). As outlined above, the experimental interventions yielded a total of 54,164 new users. However, we only observe these variables for 34,027 of them. Moreover, given the relatively small number of users in the control groups and the low baseline probability of making a referral, we are underpowered to carry out this analysis at the monthly level or distinguish by incentive amounts. Hence, we will present results averaging across all treatments and months.[7]

We estimate regressions of the referred users' characteristics on an indicator for having been referred by someone with a positive monetary incentive and an indicator for the month in which they were referred. We estimate this separately for those that were referred by a high- and by a low-engagement user. The sociodemographic characteristics are binary variables that indicate gender, age group, and occupation.[8]

Figure 8 plots the estimates for the average difference between users referred by treated customers and those referred by customers in the control. Confidence intervals at the 95% level are shown with capped spikes. The top panel are those referred by high-engagement customers, and the bottom panel were referred by low-engagement types. Across all characteristics and in both subsamples we find mostly small and insignificant differences. This indicates that, at least on these observable characteristics, users that were referred by individuals participating in a monetary reward incentive are not different, on average, from those that were organically referred without money (i.e., using only the communication nudges). Tables A10 to A13 and Tables A14 to A17 show detailed descriptives by intervention group and month, further supporting this finding.

5.2 Effect of Incentives on the Average Activity of Referred Users

We now explore whether there are differences in the level of engagement on the app between new users referred by customers in one of the treatment groups versus the controls. We examine three outcomes: transaction count, purchase count, and the likelihood of making at least one referral. We observe the first two for up to 12 months (until September 2022 for those referred in September 2021), but the latter only for up to 5 months (until January 2022 for those referred in September 2021). Using the unbalanced panel of referred users, we regress each outcome on indicators of the

[7] Among high-engagement interventions, we have a total of 1,499 referred by customers in the control groups (across all four months) and 26,246 referred by any treatment group. Among low-engagement interventions, we have a total of 401 referred by customers in the control groups and 5,881 referred by any treatment group. These numbers correspond to users for whom we observe their sociodemographic characteristics.

[8] We construct three age groups that roughly correspond to terciles of the age distribution of all users. These groups denote ages 18-27, 28-37, and 38+.

number of months since being referred interacted with an indicator for having been referred by a customer participating in a positive monetary incentive. Our excluded period is the referral month. We include indicators for the users' sign-up month (effectively restricting to within intervention variation) and monthly date fixed effects to account for overall seasonal trends in activity. As before, we estimate these regressions separately for high- and low-engagement interventions.

Figure 9 plots these estimates, shifted by the group-specific average of the outcome in the sign-up month (i.e., month zero). Solid markers denote those that were referred by a customer in any treatment group and hollow markers are those referred by individuals in the controls. Each row corresponds to a different outcome. Plots on the left are high-engagement interventions, and those on the right are low-engagement types. For transactions and purchases, point estimates are smaller for those referred by users in a treated group. However, this difference is only significant for transactions in high-engagement interventions. For the probability of making at least one referral, we find large differences between those referred by customers in a treated versus control group, with the latter having a higher probability of referring others. Overall, these findings suggest that there are some differences in the types of users that are referred by customers that received a monetary incentive and those that did not.

6 Discussion and Conclusion

This paper analyzes the impact of a referral reward program on customer acquisition in a fintech banking platform in Mexico through a series of randomized experimental interventions. Our main findings reveal that referral incentives significantly increase the likelihood of making referrals, with users being more responsive to rewards for themselves rather than their referred peers. However, users that were previously incentivized to refer were notably less likely to make new referrals, and referred users from incentivized customers exhibited lower engagement on the app during their first year. Still, users who have successfully referred someone in the past are more likely to keep referring, which underscores the importance of targeted marketing and how reward programs can identify these compliers. These results are consistent with diminishing returns of referral marketing and highlight a potential trade-off with customer quality.

Our findings provide empirical evidence supporting the idea that the effectiveness of referral programs is context-specific and influenced by various factors such as the frequency of past referrals and user engagement levels. This insight aligns with but also expands on findings from studies like Fernández-Loría et al. (2023) and Belo and Li (2022). Our paper contributes to this ongoing discussion by offering insights on the trade-offs between incentivizing referrals and maintaining customer quality. We also contribute to the identification of challenges in replicating the success of referral programs due to decreasing dynamic effects.

These results have important managerial implications. First, managers should consider designing referral programs that offer different incentive structures based on user engagement levels. Second, given the diminishing returns observed when users are repeatedly incentivized to refer, managers could implement systems to monitor referral activities and adjust incentives accordingly. By recognizing when users are becoming less responsive to incentives, firms can optimize the timing and amount of rewards to sustain referral activity without compromising the quality of new customers. Third, once monitoring is implemented, firms can identify users who refer and target the incentives to them to maximize referral likelihood. Fourth, while referral programs can drive short-term growth, the lower engagement levels of referred users from incentivized referrers suggest that a more balanced approach may be necessary. Managers could focus on strategies that not only encourage referrals but also promote long-term engagement and retention of new users.

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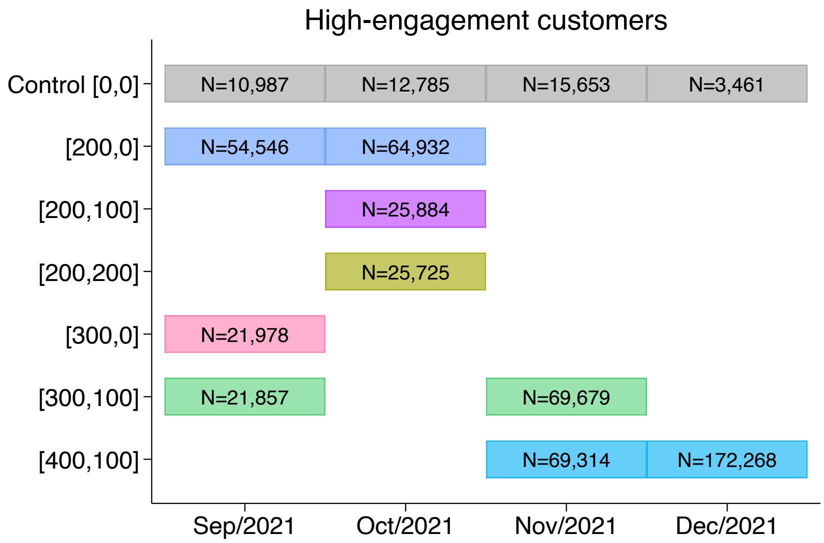
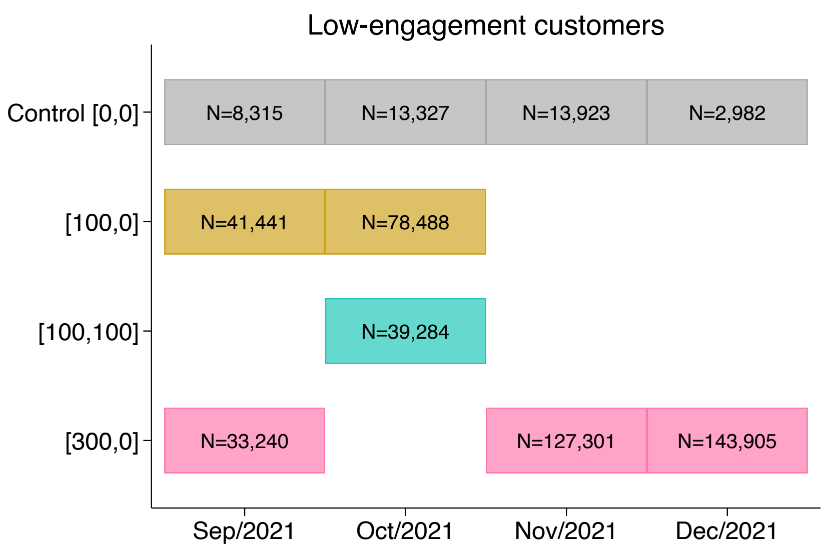
Figures and Tables

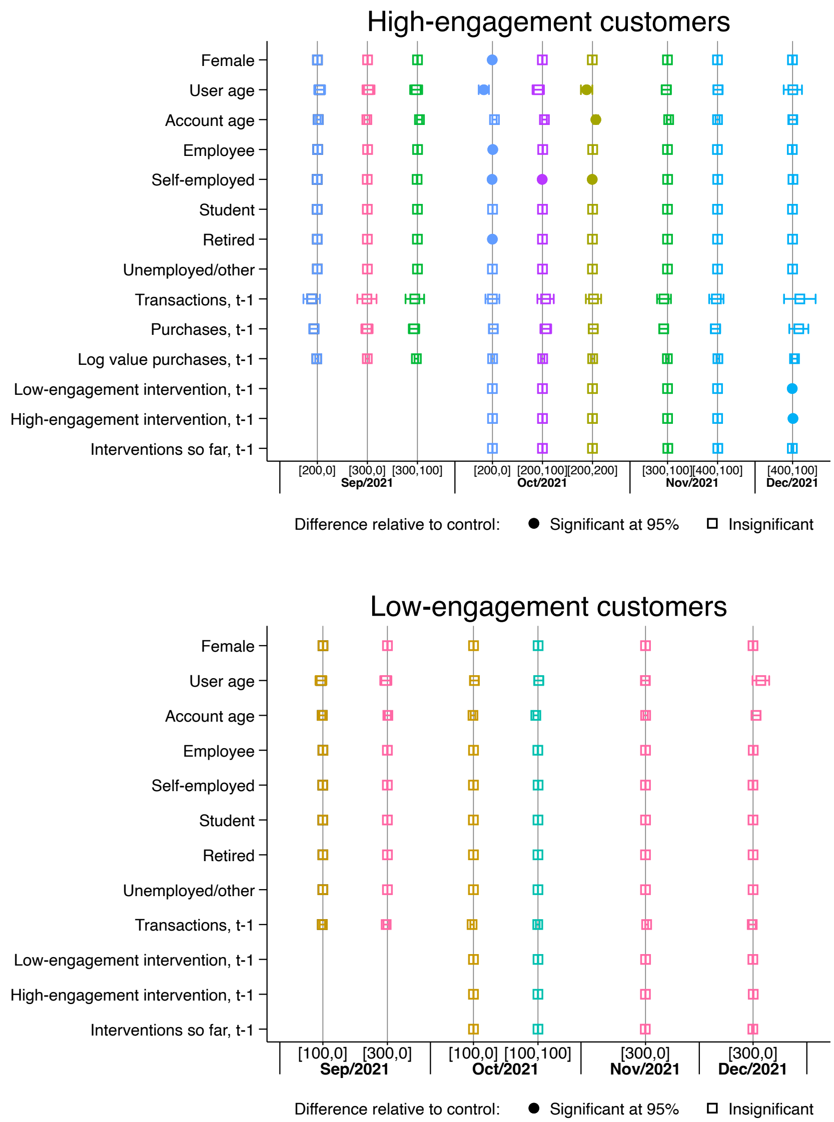
Figure 1:
Experimental Interventions and Sample Size





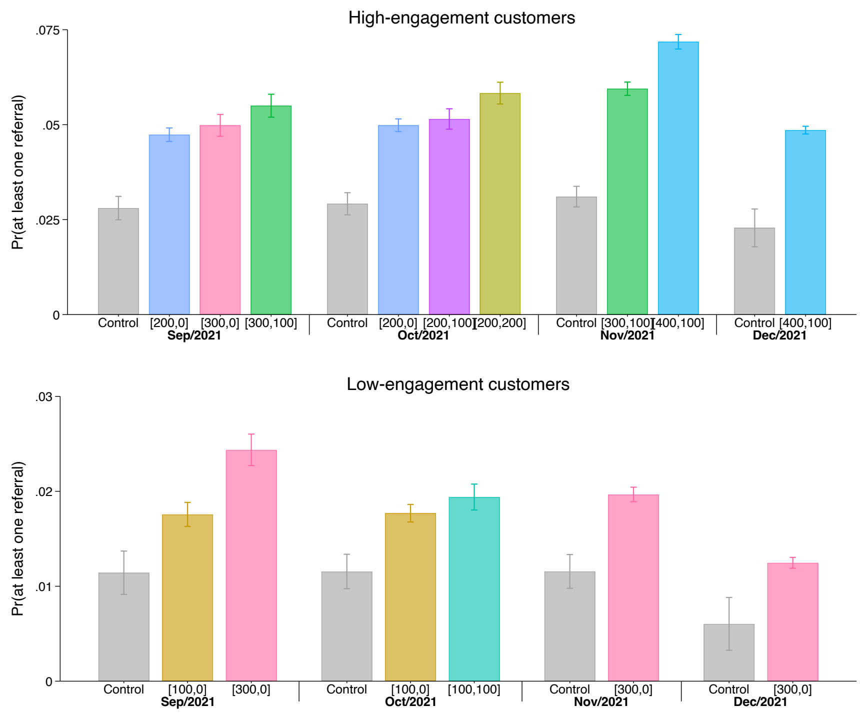
Notes: Each figure shows the experimental interventions by month. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Each cell shows the sample size for that intervention. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure 2:
Balance Tests



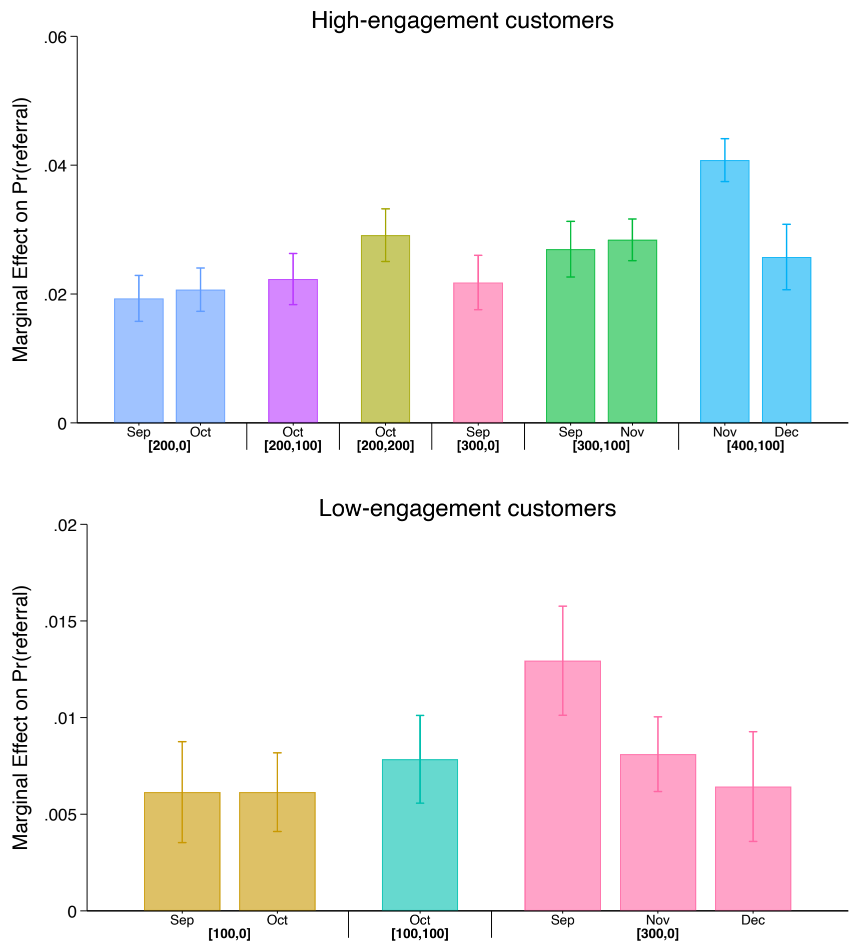
Notes: Each figure shows balance tests for each intervention against the relevant control. For each intervention, the difference relative to the control (for the same customer type in the same month) is shown. Capped spikes represent 95% confidence intervals. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Each vertical line denotes zero.

Figure 3:
Raw Averages of Referral Activity by Intervention Groups



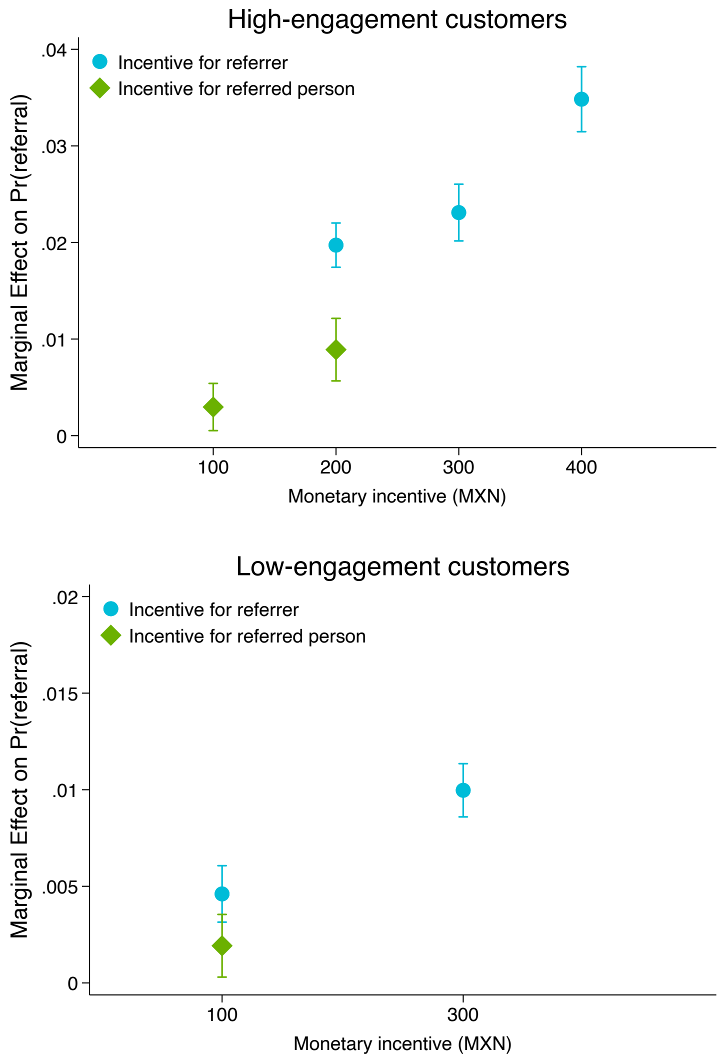
Notes: Each figure shows the share of users making at least one referral in each of the experimental interventions by month. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show the standard errors on the estimated means for each group. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure 4:
Marginal Effects of Treatments on Referral Activity by Intervention Groups



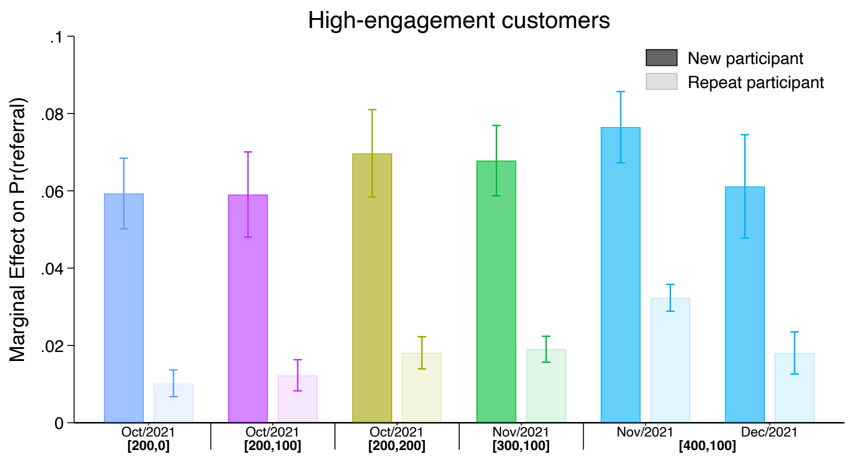
Notes: Each figure shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated directly from a linear probability model (see equation 1 in the main text). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

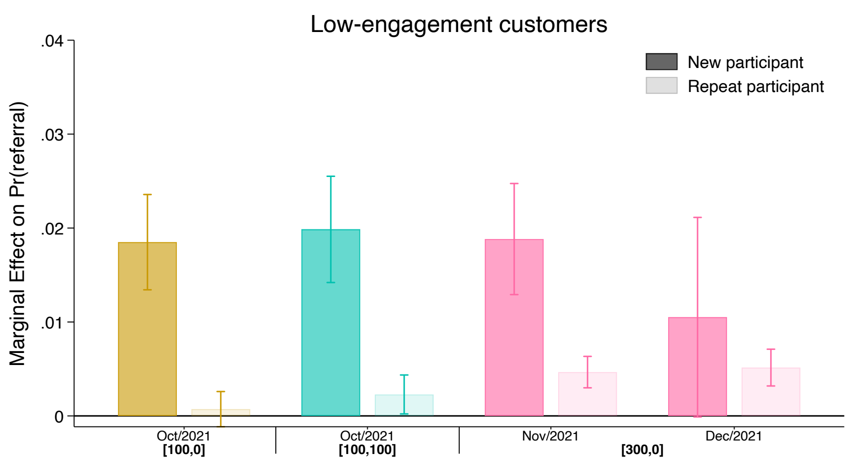
Figure 5:
Average Marginal Effects of Monetary Incentives on Referral Activity



Notes: Each figure shows the average marginal effect across interventions of each monetary incentive amount on the probability of making at least one referral. Estimates are shown from an OLS specification that includes indicators for each value of w and for each value of z as regressors, instead of indicators for each treatment group (and month fixed effects as before). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred.

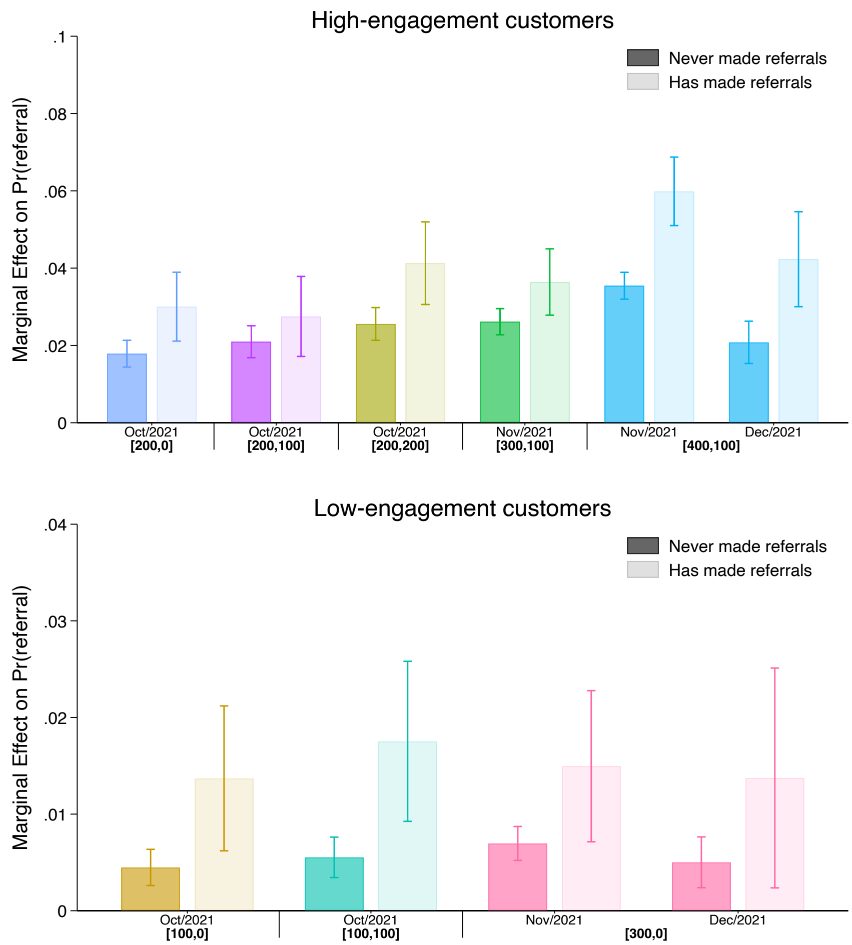
Figure 6:
Heterogeneity of Marginal Effects of Treatments on Referral Activity
by Past Participation in Interventions





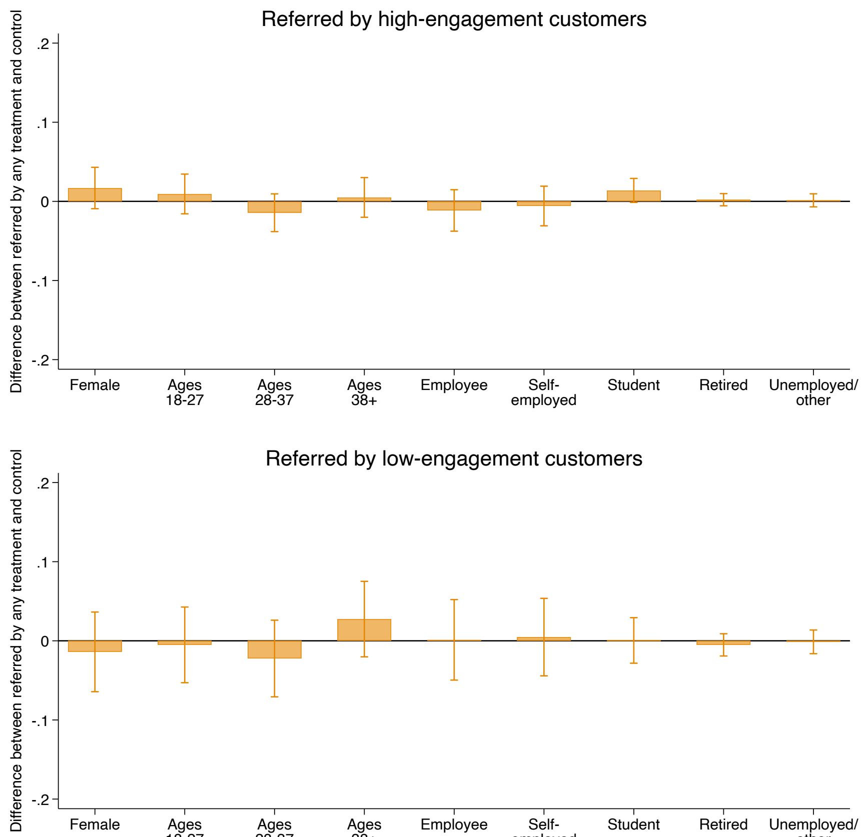
Notes: Each figure shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated directly from a linear probability model (see equation 1 in the main text). Effects are shown separately for new participants (i.e., users that had never been in any intervention before) and repeat participants. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure 7:
Heterogeneity of Marginal Effects of Treatments on Referral Activity
by Past Referral Activity



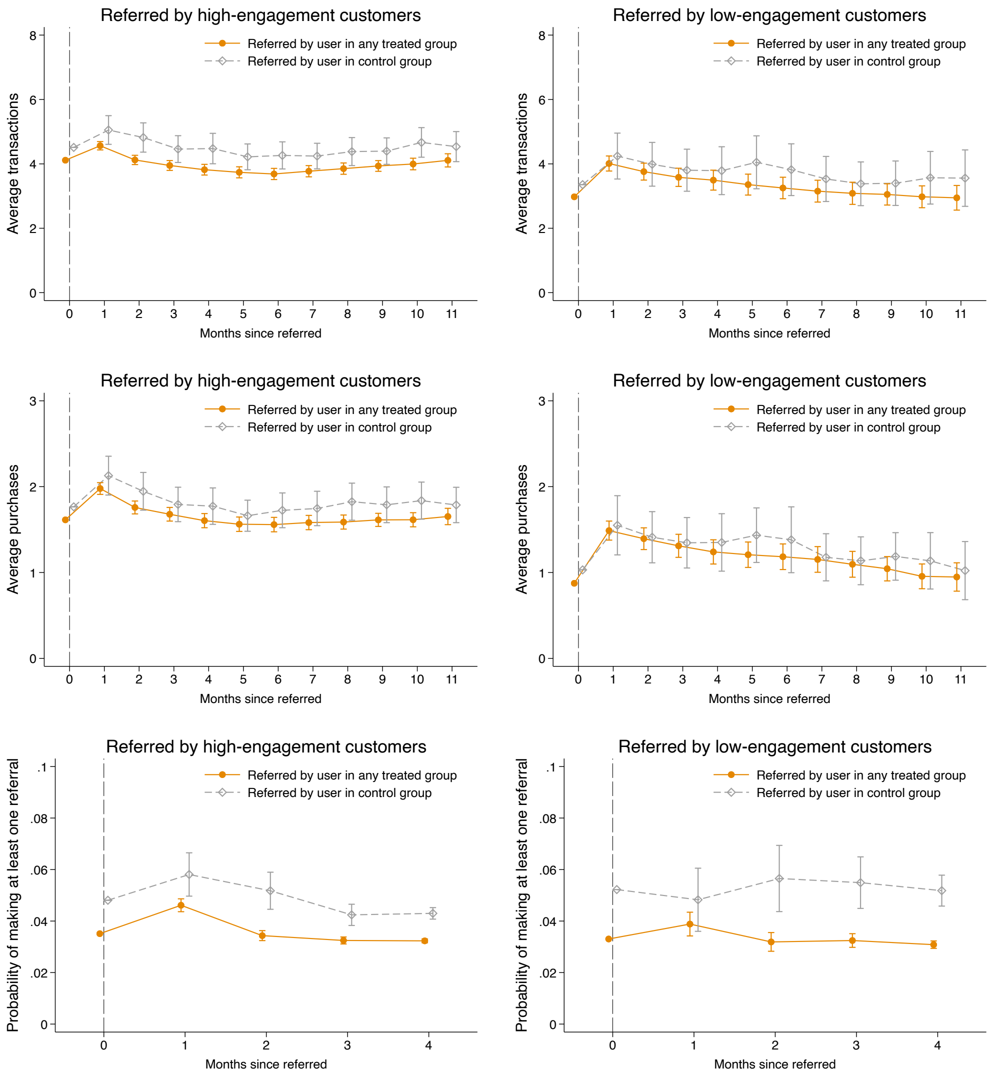
Notes: Each figure shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated directly from a linear probability model (see equation 1 in the main text). Effects are shown separately for experiment participants that have made referrals prior to the intervention and those that have not. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure 8:
Average Characteristics of New Users Referred by Intervention Participants in Treated vs Control Groups



Notes: Each figure shows the average difference across time-invariant characteristics between new users referred by intervention participants assigned to a treatment group (any positive monetary incentive) and the control group (zero monetary incentive). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals on the estimated difference in means between the groups. Differences are calculated between any treatment group and the corresponding control within a given month, and are then averaged over all months.

Figure 9:
Average Monthly Activity of New Users Referred by Intervention Participants in Treated vs Control Groups

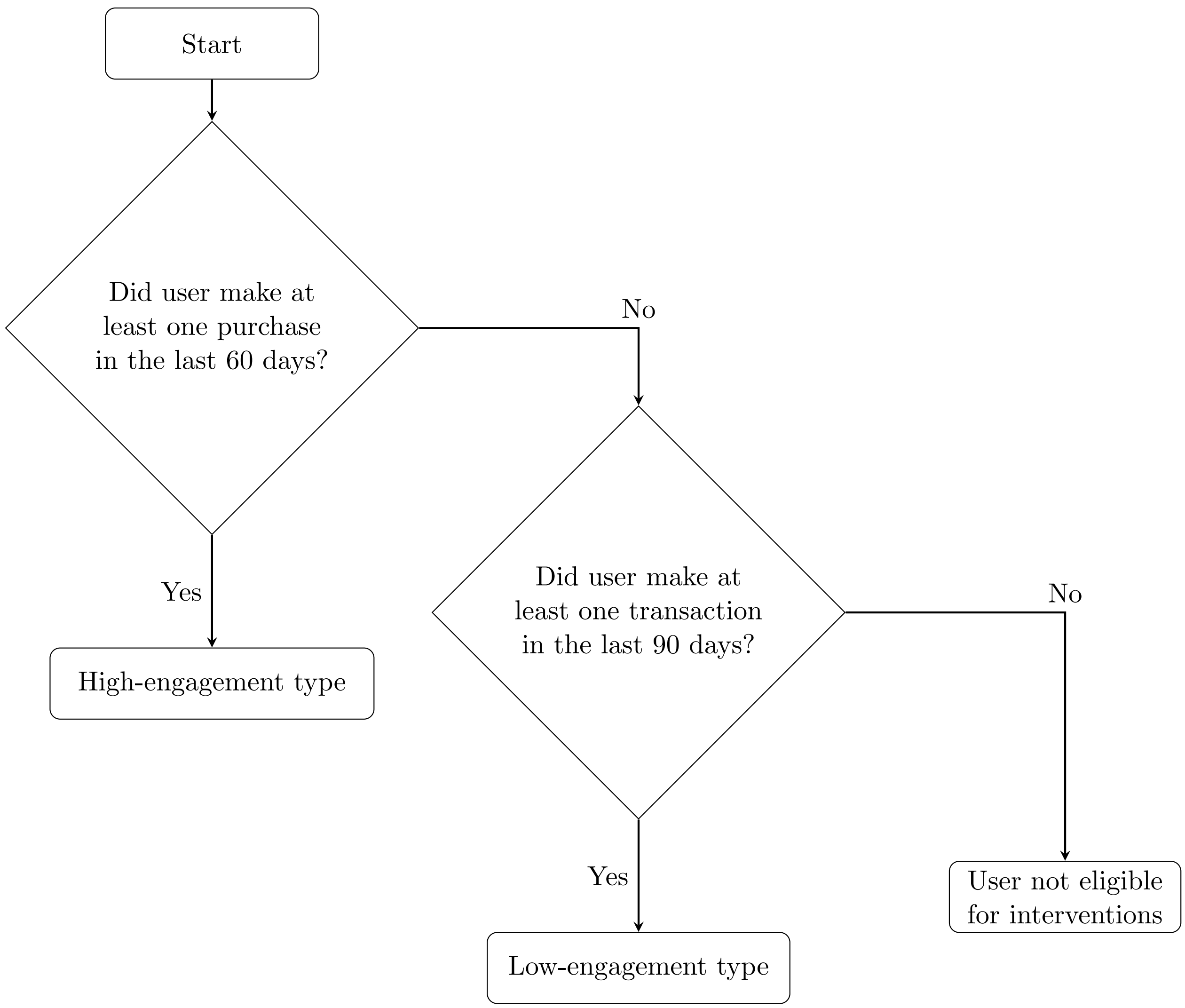


Notes: Each figure shows the average monthly activity of new users referred by intervention participants assigned to a treatment group (any positive monetary incentive) and those referred by users in the control group (zero monetary incentive). Monthly estimates shown from a regression with referral month fixed effects and date fixed effects. Capped spikes show 95% confidence intervals from robust standard errors. The top plots show average transactions, the middle plots show average purchases, and the bottom plots are the probability of making at least one referral. Plots on the left are for new users referred by high-engagement customers; plots on the right are for those referred by low-engagement. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days.

Appendix for Online Publication

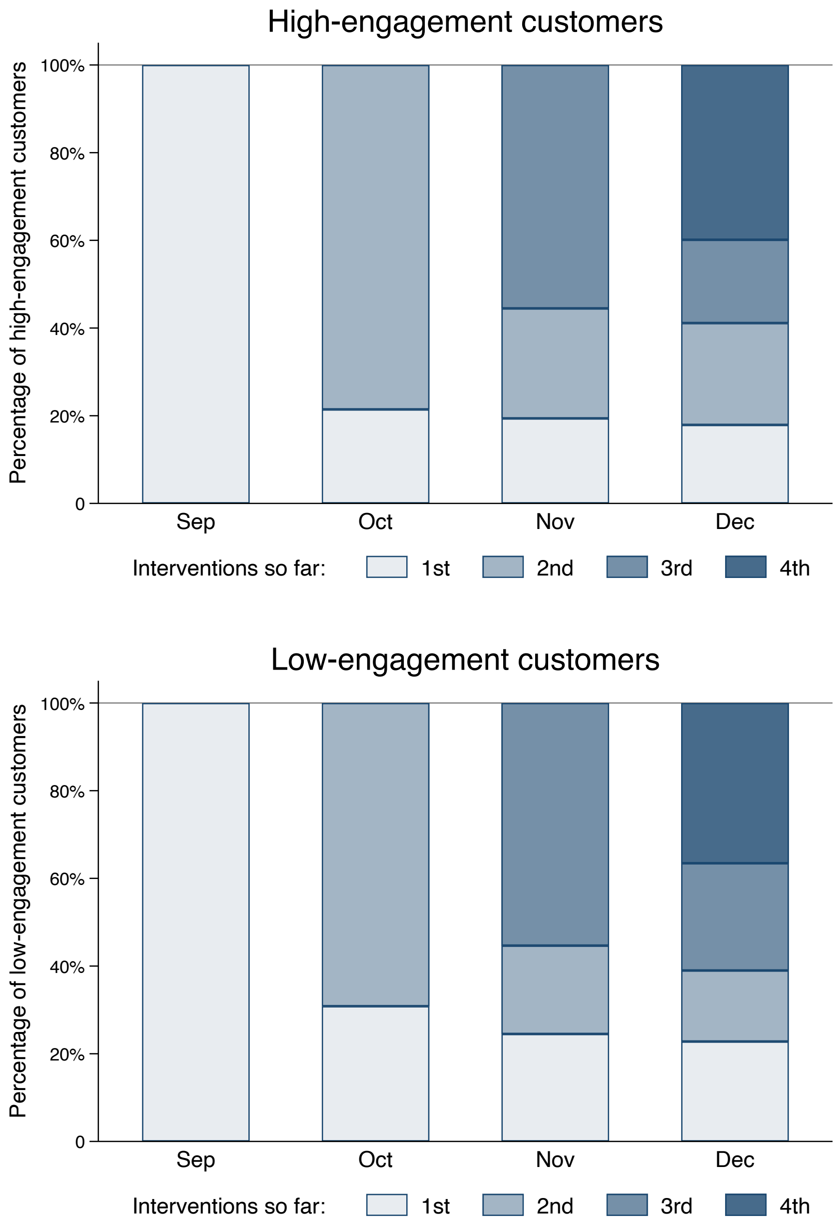
A Additional Details on the Interventions

Figure A1:
Definition of Eligibility for Experimental Interventions



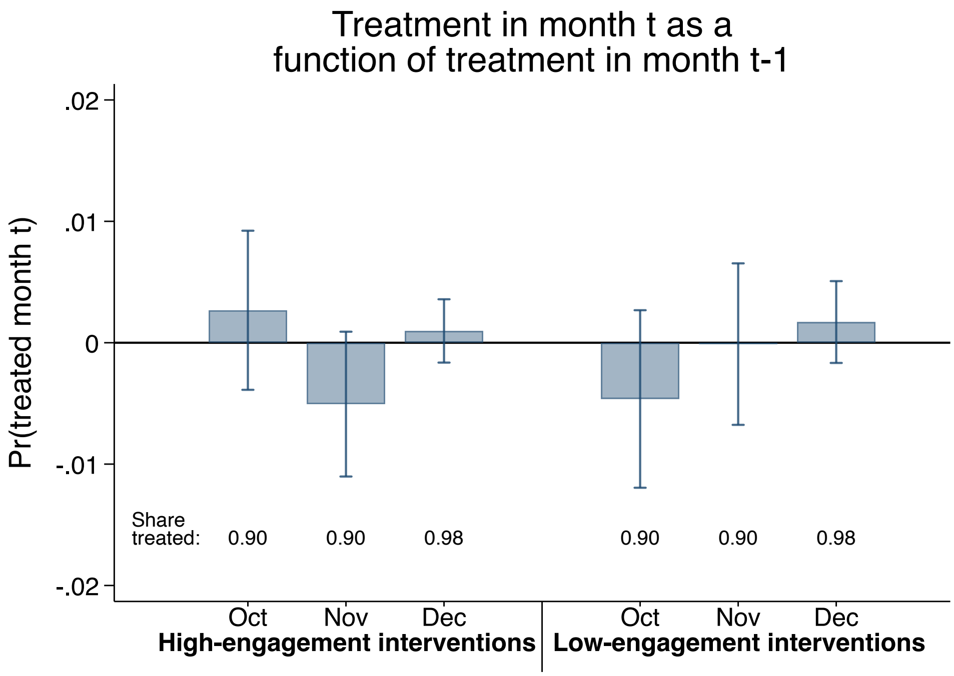
Notes: This figure shows a flowchart depicting how eligibility for the interventions was determined before each of the experimental months (September through December 2021).

Figure A2:
Share of Participants by Number of Cumulative Experimental Interventions



Notes: Each figure shows the share of customers that are participating for the first, second, third, or fourth time in any of the experimental interventions by month. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Each cell shows the sample size for that intervention.

Figure A3:
Serial Correlation in Treatment Assignment



Notes: This plot shows the differential probability of being treated (i.e., receiving a positive monetary incentive) in month t if the user was treated in month $t-1$. We distinguish between interventions for high-engagement and low-engagement customers. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Each bar corresponds to the coefficient from a separate regression of an indicator for being treated in month t on an indicator for being treated in month $t-1$, conditional on having participated in the interventions (regardless of treatment or control) in both months. Bars represent 95% confidence intervals from robust standard errors. For each sample, we also show the share that was treated in each month.

B Balance Tests

Table A1:
Descriptives: High-Engagement Users in September 2021

	Intervention group			
	[200,0]	[300,0]	[300,100]	Control
Female	0.322	0.326	0.323	0.318
	(0.467)	(0.469)	(0.467)	(0.466)
Age	32.019	31.971	31.877	31.927
	(10.454)	(10.526)	(10.411)	(10.503)
Months since account created	4.997	4.942	5.046	4.964
	(4.544)	(4.430)	(4.606)	(4.497)
Occupation: Employee	0.538	0.536	0.534	0.528
	(0.499)	(0.499)	(0.499)	(0.499)
Occupation: Self-employed/owns business	0.330	0.331	0.326	0.336
	(0.470)	(0.471)	(0.469)	(0.473)
Occupation: Student	0.107	0.109	0.112	0.111
	(0.309)	(0.312)	(0.316)	(0.314)
Occupation: Retired	0.009	0.009	0.009	0.010
	(0.094)	(0.093)	(0.096)	(0.098)
Occupation: Unemployed/other	0.016	0.015	0.018	0.015
	(0.125)	(0.123)	(0.134)	(0.123)
Total transactions last month	9.593	9.803	9.717	9.821
	(15.183)	(17.462)	(15.839)	(15.970)
Total purchases last month	4.689	4.808	4.689	4.825
	(8.751)	(11.008)	(8.925)	(8.946)
Log value of purchases last month	4.534	4.552	4.513	4.554
	(3.128)	(3.124)	(3.135)	(3.117)
Participated in low-engagement interventions last month	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Participated in high-engagement interventions last month	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Total interventions up to last month	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	54,546	21,978	21,857	10,987

Notes: This table shows descriptives for high-engagement users that participated in interventions in September 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A2:
Descriptives: High-Engagement Users in October 2021

	Intervention group			
	[200,0]	[200,100]	[200,200]	Control
Female	0.328	0.332	0.330	0.337
	(0.469)	(0.471)	(0.470)	(0.473)
Age	32.040	32.216	32.151	32.385
	(10.556)	(10.659)	(10.588)	(10.852)
Months since account created	4.962	4.959	5.016	4.881
	(4.564)	(4.578)	(4.599)	(4.517)
Occupation: Employee	0.545	0.542	0.540	0.532
	(0.498)	(0.498)	(0.498)	(0.499)
Occupation: Self-employed/owns business	0.326	0.329	0.330	0.340
	(0.469)	(0.470)	(0.470)	(0.474)
Occupation: Student	0.104	0.101	0.104	0.099
	(0.305)	(0.301)	(0.305)	(0.299)
Occupation: Retired	0.009	0.011	0.010	0.011
	(0.094)	(0.105)	(0.098)	(0.106)
Occupation: Unemployed/other	0.015	0.017	0.016	0.017
	(0.124)	(0.130)	(0.126)	(0.129)
Total transactions last month	8.352	8.478	8.394	8.354
	(14.052)	(16.525)	(13.524)	(14.397)
Total purchases last month	4.134	4.230	4.126	4.097
	(8.552)	(12.071)	(7.574)	(8.692)
Log value of purchases last month	4.181	4.181	4.182	4.174
	(3.246)	(3.252)	(3.229)	(3.250)
Participated in low-engagement interventions last month	0.098	0.100	0.101	0.100
	(0.297)	(0.300)	(0.301)	(0.301)
Participated in high-engagement interventions last month	0.720	0.718	0.716	0.717
	(0.449)	(0.450)	(0.451)	(0.450)
Total interventions up to last month	0.818	0.818	0.817	0.818
	(0.386)	(0.386)	(0.387)	(0.386)
Observations	64,932	25,884	25,725	12,785

Notes: This table shows descriptives for high-engagement users that participated in interventions in October 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A3:
Descriptives: High-Engagement Users in November 2021

	Intervention group		
	[300,100]	[400,100]	Control
Female	0.336	0.337	0.339
	(0.472)	(0.473)	(0.473)
Age	32.264	32.333	32.315
	(10.653)	(10.709)	(10.690)
Months since account created	4.976	4.929	4.930
	(4.592)	(4.583)	(4.568)
Occupation: Employee	0.549	0.546	0.550
	(0.498)	(0.498)	(0.497)
Occupation: Self-employed/owns business	0.328	0.331	0.325
	(0.470)	(0.470)	(0.468)
Occupation: Student	0.098	0.099	0.099
	(0.297)	(0.298)	(0.299)
Occupation: Retired	0.010	0.010	0.010
	(0.101)	(0.099)	(0.097)
Occupation: Unemployed/other	0.015	0.015	0.016
	(0.122)	(0.122)	(0.126)
Total transactions last month	9.584	9.678	9.725
	(15.266)	(17.901)	(15.924)
Total purchases last month	4.608	4.679	4.761
	(8.829)	(12.899)	(10.174)
Log value of purchases last month	4.468	4.488	4.474
	(3.227)	(3.225)	(3.238)
Participated in low-engagement interventions last month	0.125	0.126	0.125
	(0.331)	(0.331)	(0.330)
Participated in high-engagement interventions last month	0.701	0.702	0.700
	(0.458)	(0.457)	(0.458)
Total interventions up to last month	1.398	1.397	1.387
	(0.766)	(0.764)	(0.767)
Observations	69,679	69,314	15,653

Notes: This table shows descriptives for high-engagement users that participated in interventions in November 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A4:
Descriptives: High-Engagement Users in December 2021

	Intervention group	
	[400,100]	Control
Female	0.343	0.348
	(0.475)	(0.476)
Age	32.327	32.316
	(10.761)	(10.846)
Months since account created	5.033	5.025
	(4.665)	(4.637)
Occupation: Employee	0.546	0.556
	(0.498)	(0.497)
Occupation: Self-employed/owns business	0.330	0.315
	(0.470)	(0.465)
Occupation: Student	0.099	0.102
	(0.298)	(0.303)
Occupation: Retired	0.011	0.011
	(0.102)	(0.102)
Occupation: Unemployed/other	0.015	0.016
	(0.123)	(0.125)
Total transactions last month	12.314	12.024
	(20.824)	(18.411)
Total purchases last month	6.037	5.788
	(14.190)	(11.081)
Log value of purchases last month	5.028	4.951
	(3.210)	(3.219)
Participated in low-engagement interventions last month	0.120	0.134
	(0.325)	(0.341)
Participated in high-engagement interventions last month	0.720	0.704
	(0.449)	(0.457)
Total interventions up to last month	1.866	1.876
	(1.115)	(1.121)
Observations	172,268	3,461

Notes: This table shows descriptives for high-engagement users that participated in interventions in December 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A5:
Descriptives: Low-Engagement Users in September 2021

	Intervention group		
	[100,0]	[300,0]	Control
Female	0.367	0.365	0.361
	(0.482)	(0.481)	(0.480)
Age	33.520	33.536	33.609
	(10.727)	(10.889)	(10.755)
Months since account created	4.928	4.976	4.955
	(5.624)	(5.709)	(5.721)
Occupation: Employee	0.548	0.545	0.546
	(0.498)	(0.498)	(0.498)
Occupation: Self-employed/owns business	0.353	0.353	0.356
	(0.478)	(0.478)	(0.479)
Occupation: Student	0.072	0.073	0.073
	(0.258)	(0.260)	(0.261)
Occupation: Retired	0.011	0.012	0.010
	(0.104)	(0.107)	(0.100)
Occupation: Unemployed/other	0.016	0.017	0.015
	(0.126)	(0.130)	(0.123)
Total transactions last month	2.107	2.076	2.132
	(5.292)	(5.139)	(4.730)
Participated in low-engagement interventions last month	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Participated in high-engagement interventions last month	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Total interventions up to last month	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	41,441	33,240	8,315

Notes: This table shows descriptives for low-engagement users that participated in interventions in September 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A6:
Descriptives: Low-Engagement Users in October 2021

	Intervention group		
	[100,0]	[100,100]	Control
Female	0.367	0.369	0.362
	(0.482)	(0.483)	(0.480)
Age	33.516	33.506	33.471
	(10.791)	(10.787)	(10.742)
Months since account created	5.307	5.230	5.329
	(5.570)	(5.522)	(5.618)
Occupation: Employee	0.554	0.544	0.549
	(0.497)	(0.498)	(0.498)
Occupation: Self-employed/owns business	0.350	0.356	0.350
	(0.477)	(0.479)	(0.477)
Occupation: Student	0.070	0.074	0.073
	(0.255)	(0.261)	(0.261)
Occupation: Retired	0.011	0.011	0.011
	(0.105)	(0.103)	(0.107)
Occupation: Unemployed/other	0.015	0.015	0.015
	(0.122)	(0.123)	(0.123)
Total transactions last month	1.269	1.322	1.331
	(3.507)	(3.897)	(4.320)
Participated in low-engagement interventions last month	0.597	0.598	0.596
	(0.490)	(0.490)	(0.491)
Participated in high-engagement interventions last month	0.170	0.167	0.169
	(0.376)	(0.373)	(0.374)
Total interventions up to last month	0.767	0.765	0.765
	(0.423)	(0.424)	(0.424)
Observations	78,488	39,284	13,327

Notes: This table shows descriptives for low-engagement users that participated in interventions in October 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A7:
Descriptives: Low-Engagement Users in November 2021

	Intervention group	
	[300,100]	Control
Female	0.374	0.373
	(0.484)	(0.484)
Age	33.468	33.473
	(10.806)	(10.737)
Months since account created	5.539	5.533
	(5.762)	(5.764)
Occupation: Employee	0.553	0.553
	(0.497)	(0.497)
Occupation: Self-employed/owns business	0.349	0.351
	(0.477)	(0.477)
Occupation: Student	0.071	0.069
	(0.257)	(0.254)
Occupation: Retired	0.011	0.012
	(0.104)	(0.107)
Occupation: Unemployed/other	0.015	0.016
	(0.122)	(0.125)
Total transactions last month	1.450	1.398
	(4.204)	(3.526)
Participated in low-engagement interventions last month	0.634	0.631
	(0.482)	(0.482)
Participated in high-engagement interventions last month	0.179	0.182
	(0.383)	(0.386)
Total interventions up to last month	1.408	1.419
	(0.785)	(0.785)
Observations	127,301	13,923

Notes: This table shows descriptives for low-engagement users that participated in interventions in November 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

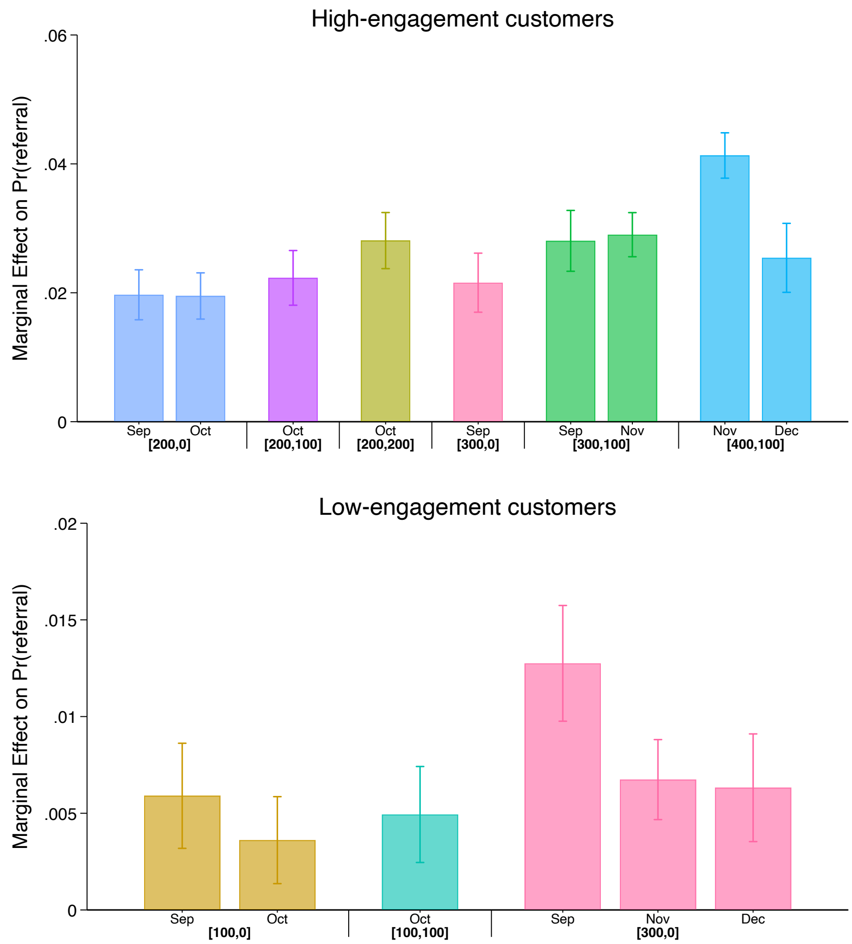
Table A8:
Descriptives: Low-Engagement Users in December 2021

	Intervention group	
	[300,0]	Control
Female	0.386	0.389
	(0.487)	(0.488)
Age	33.536	33.173
	(10.968)	(10.695)
Months since account created	5.650	5.509
	(5.868)	(5.740)
Occupation: Employee	0.556	0.548
	(0.497)	(0.498)
Occupation: Self-employed/owns business	0.348	0.354
	(0.476)	(0.478)
Occupation: Student	0.069	0.072
	(0.253)	(0.259)
Occupation: Retired	0.012	0.011
	(0.107)	(0.103)
Occupation: Unemployed/other	0.015	0.015
	(0.122)	(0.123)
Total transactions last month	1.610	1.649
	(4.939)	(4.278)
Participated in low-engagement interventions last month	0.602	0.612
	(0.489)	(0.487)
Participated in high-engagement interventions last month	0.220	0.213
	(0.414)	(0.409)
Total interventions up to last month	1.877	1.887
	(1.111)	(1.110)
Observations	143,905	2,982

Notes: This table shows descriptives for low-engagement users that participated in interventions in December 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

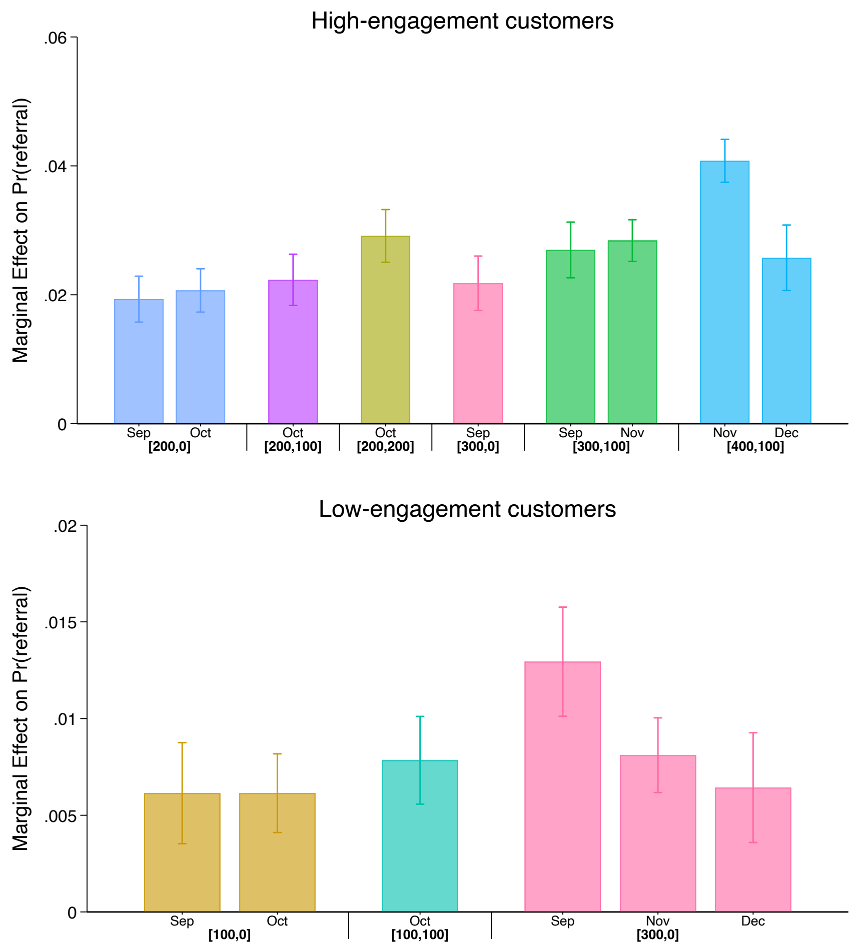
C Robustness Checks

Figure A4:
Robustness to Controls of Marginal Effects of Treatments on Referral Activity



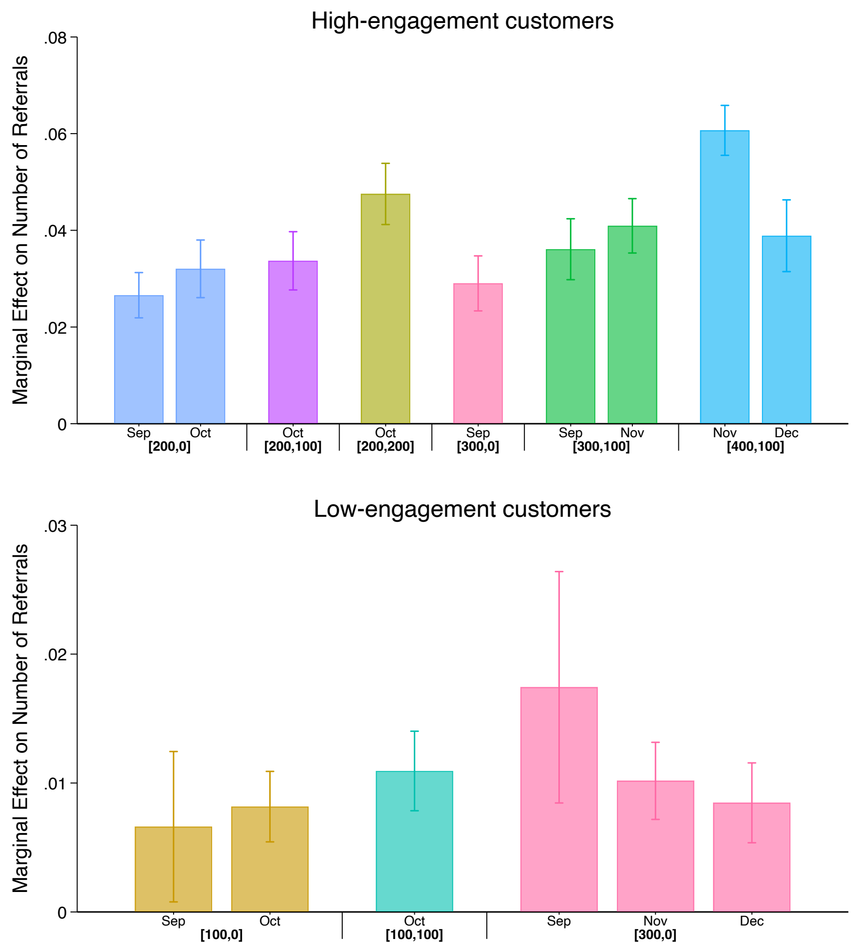
Notes: Each figure shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated directly from a linear probability model (see equation 1 in the main text). Specifications control for all variables listed in Figure 2. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure A5:
Robustness to Logit Specification for Marginal Effects of Treatments on Referral Activity



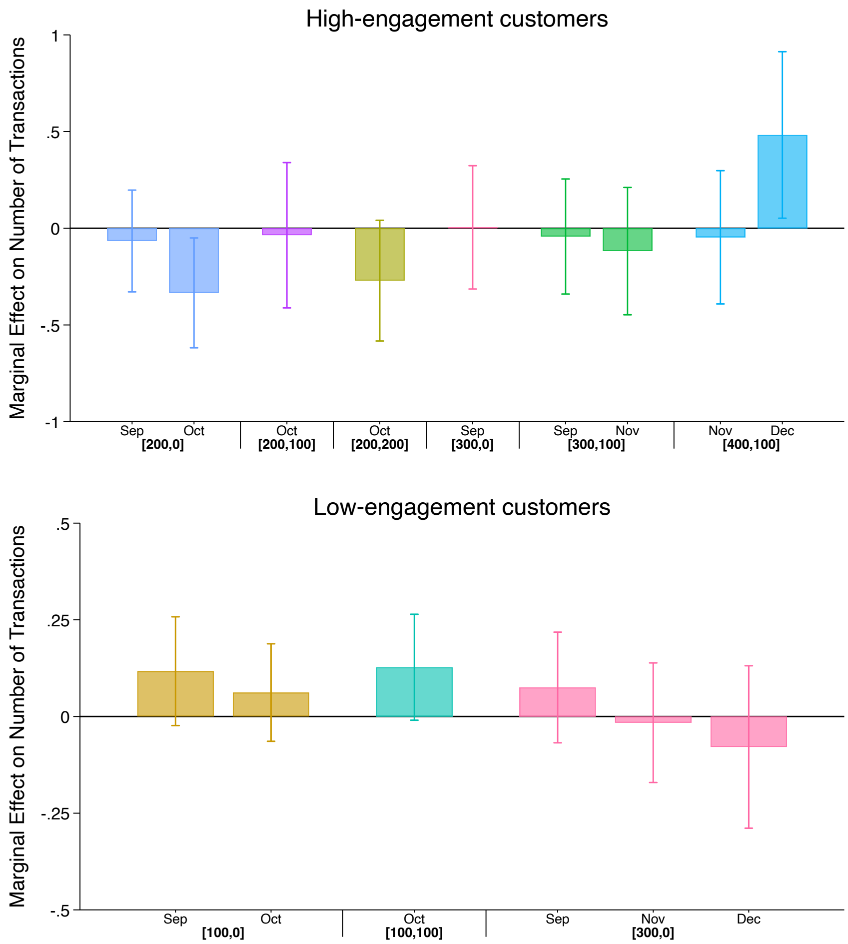
Notes: Each figure shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated from a Logit specification equivalent to equation 1. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure A6:
Robustness to Poisson Specification for Marginal Effects of Treatments on Referral Activity



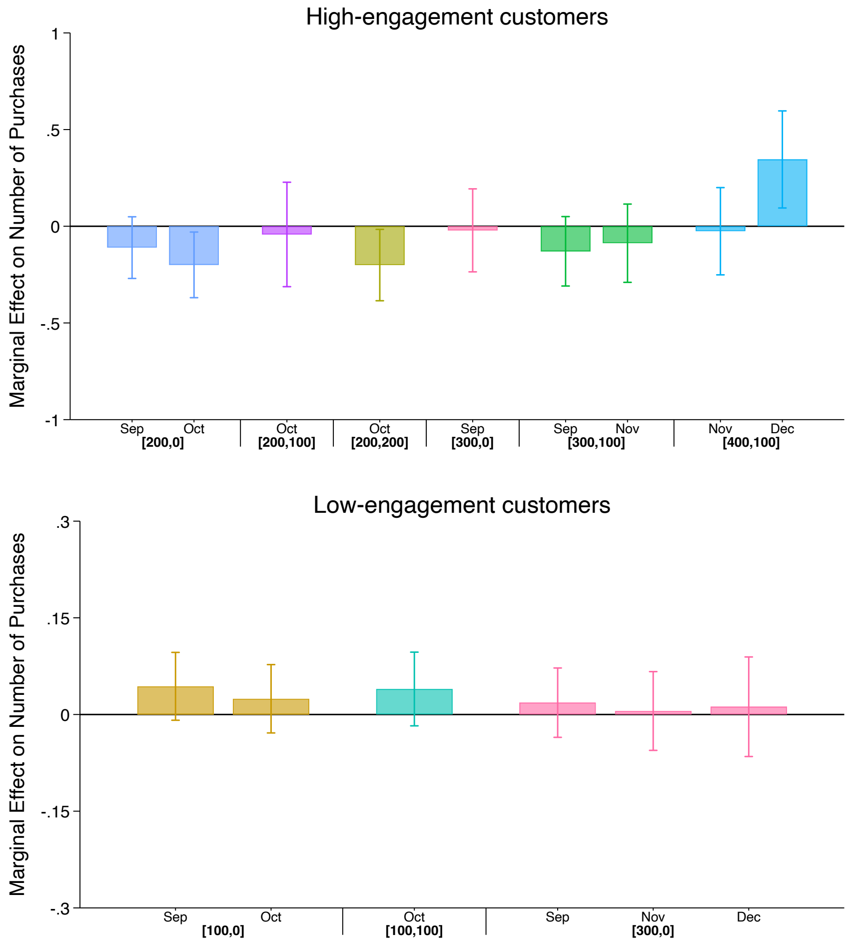
Notes: Each figure shows the marginal effect of each treatment on the number of referrals made for each of the experimental interventions by month. Marginal effects are calculated from a Poisson specification equivalent to equation 1. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure A7:
Marginal Effects of Treatments on Own Number of Transactions



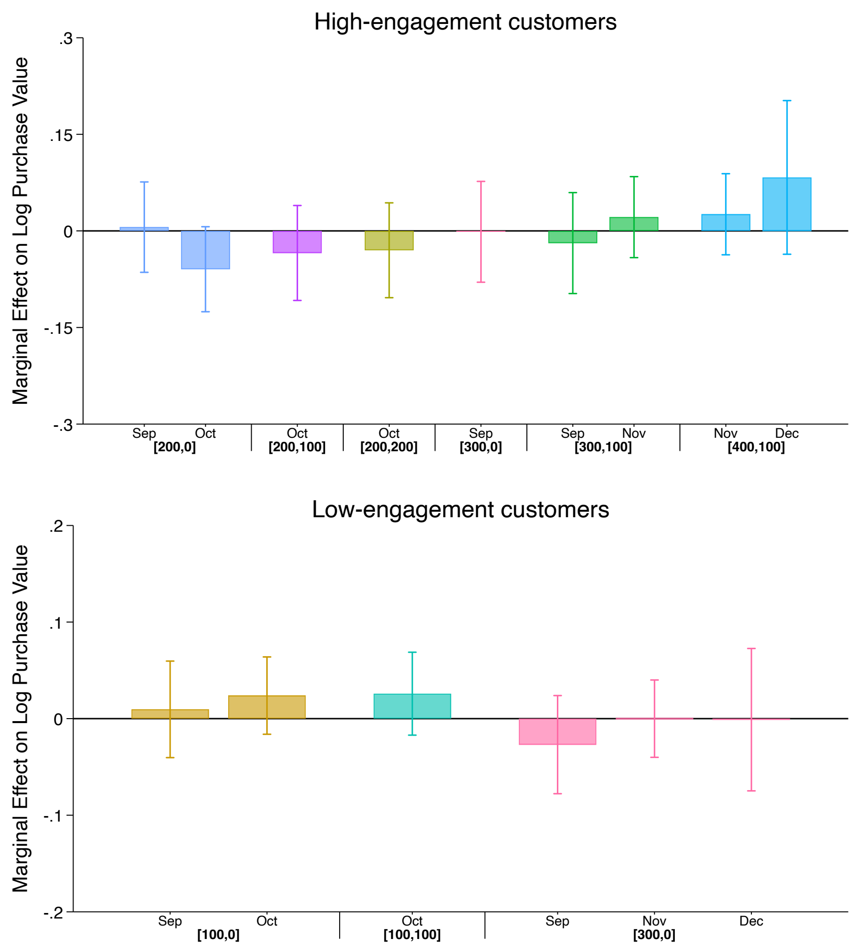
Notes: Each figure shows the marginal effect of each treatment on the user's own number of transactions for each of the experimental interventions by month. Marginal effects are calculated from an OLS specification (see equation 1 in the main text). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure A8:
Marginal Effects of Treatments on Own Number of Purchases



Notes: Each figure shows the marginal effect of each treatment on the user's own number of purchases for each of the experimental interventions by month. Marginal effects are calculated from an OLS specification (see equation 1 in the main text). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Figure A9:
Marginal Effects of Treatments on Own Purchase Value



Notes: Each figure shows the marginal effect of each treatment on the value of the user's own purchases for each of the experimental interventions by month. Purchase value is log-transformed using the inverse hyperbolic sine function to allow for zero values. Marginal effects are calculated from an OLS specification (see equation 1 in the main text). High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Capped spikes show 95% confidence intervals from robust standard errors. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.

Table A9:
Robustness to Panel Experiment Structure of Marginal Effects of Treatments on Referral Activity

	September		October		November		December	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High-engagement customers								
$[200, 0]$	0.019***	n.a.	0.021***	0.025***				
	(0.002)	n.a.	(0.002)	(0.005)				
$[200, 100]$			0.022***	0.034***				
			(0.002)	(0.007)				
$[200, 200]$			0.029***	0.033***				
			(0.002)	(0.007)				
$[300, 0]$	0.022***	n.a.						
	(0.002)	n.a.						
$[300, 100]$	0.027***	n.a.			0.028***	0.022***		
	(0.002)	n.a.			(0.002)	(0.006)		
$[400, 100]$					0.041***	0.037***	0.026***	0.015
					(0.002)	(0.006)	(0.003)	(0.011)
Augmented model		X		X		X		X
Control mean	0.028	n.a.	0.029	0.029	0.031	0.031	0.023	0.023
N	109,368	n.a.	129,326	129,326	154,646	154,646	175,729	175,729
Panel B: Low-engagement customers								
$[100, 0]$	0.006***	n.a.	0.006***	0.002				
	(0.001)	n.a.	(0.001)	(0.003)				
$[100, 100]$			0.008***	0.005				
			(0.001)	(0.004)				
$[300, 0]$	0.013***	n.a.			0.008***	0.003	0.006***	0.009***
	(0.001)	n.a.			(0.001)	(0.003)	(0.001)	(0.001)
Augmented model		X		X		X		X
Control mean	0.011	n.a.	0.012	0.012	0.012	0.012	0.006	0.006
N	82,996	n.a.	131,099	131,099	141,224	141,224	146,887	146,887

Notes: This table shows the marginal effect of each treatment on the probability of making at least one referral for each of the experimental interventions by month. Marginal effects are calculated from a linear probability model (see equation 1 in the main text), corresponding to all odd-numbered columns. Even-numbered columns report marginal effects from an augmented linear regression that controls for treatment assignments in the previous months (including non-eligibility last month) and the full interactions between last month's and this month's assignment. Interventions prior to September are unobserved so that this augmented specification is not available (n.a.) in column 2. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. From the remaining customers, low-engagement customers are those that had at least one transaction in the last 90 days. Robust standard errors are shown in parentheses. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Characteristics of Users Referred by Intervention Participants

Table A10:
Descriptives of New Users: Referred by High-Engagement Users in September 2021

	Intervention group			
	[200,0]	[300,0]	[300,100]	Control
Female	0.544	0.522	0.558	0.518
	(0.498)	(0.500)	(0.497)	(0.500)
Age	35.503	35.286	35.558	34.738
	(13.391)	(13.180)	(13.488)	(13.728)
Ages 18-27	0.350	0.353	0.363	0.398
	(0.477)	(0.478)	(0.481)	(0.490)
Ages 28-37	0.282	0.281	0.269	0.244
	(0.450)	(0.450)	(0.444)	(0.430)
Ages 38+	0.368	0.366	0.367	0.357
	(0.482)	(0.482)	(0.482)	(0.480)
Employee	0.493	0.505	0.506	0.471
	(0.500)	(0.500)	(0.500)	(0.500)
Self-employed/owns business	0.352	0.332	0.344	0.357
	(0.478)	(0.471)	(0.475)	(0.480)
Student	0.105	0.099	0.099	0.122
	(0.307)	(0.298)	(0.299)	(0.328)
Retired	0.026	0.025	0.028	0.023
	(0.160)	(0.155)	(0.165)	(0.149)
Unemployed/other	0.024	0.039	0.022	0.027
	(0.153)	(0.194)	(0.147)	(0.163)
Observations	2,702	1,096	1,173	442

Notes: This table shows descriptives for new users that were referred by high-engagement users that participated in interventions in September 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A11:
Descriptives of New Users: Referred by High-Engagement Users in October 2021

	Intervention group			
	[200,0]	[200,100]	[200,200]	Control
Female	0.556	0.575	0.546	0.554
	(0.497)	(0.494)	(0.498)	(0.498)
Age	34.520	34.794	34.668	35.177
	(12.650)	(12.985)	(12.770)	(12.256)
Ages 18-27	0.373	0.374	0.367	0.328
	(0.484)	(0.484)	(0.482)	(0.470)
Ages 28-37	0.285	0.271	0.282	0.311
	(0.452)	(0.445)	(0.450)	(0.464)
Ages 38+	0.342	0.355	0.351	0.360
	(0.475)	(0.479)	(0.478)	(0.481)
Employee	0.508	0.494	0.499	0.505
	(0.500)	(0.500)	(0.500)	(0.501)
Self-employed/owns business	0.337	0.338	0.343	0.371
	(0.473)	(0.473)	(0.475)	(0.484)
Student	0.109	0.115	0.116	0.081
	(0.311)	(0.319)	(0.320)	(0.273)
Retired	0.021	0.027	0.018	0.021
	(0.142)	(0.162)	(0.134)	(0.145)
Unemployed/other	0.026	0.027	0.024	0.021
	(0.160)	(0.162)	(0.152)	(0.145)
Observations	3,156	1,300	1,486	469

Notes: This table shows descriptives for new users that were referred by high-engagement users that participated in interventions in October 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A12:
Descriptives of New Users: Referred by High-Engagement Users in November 2021

	Intervention group		
	[300,100]	[400,100]	Control
Female	0.573	0.551	0.552
	(0.495)	(0.497)	(0.498)
Age	34.842	35.108	34.888
	(12.860)	(13.271)	(12.569)
Ages 18-27	0.363	0.368	0.339
	(0.481)	(0.482)	(0.474)
Ages 28-37	0.284	0.270	0.323
	(0.451)	(0.444)	(0.468)
Ages 38+	0.353	0.362	0.339
	(0.478)	(0.481)	(0.474)
Employee	0.498	0.494	0.534
	(0.500)	(0.500)	(0.499)
Self-employed/owns business	0.353	0.349	0.329
	(0.478)	(0.477)	(0.470)
Student	0.098	0.105	0.082
	(0.297)	(0.307)	(0.274)
Retired	0.025	0.023	0.026
	(0.157)	(0.151)	(0.159)
Unemployed/other	0.026	0.028	0.030
	(0.160)	(0.166)	(0.170)
Observations	3,566	4,180	502

Notes: This table shows descriptives for new users that were referred by high-engagement users that participated in interventions in November 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A13:
Descriptives of New Users: Referred by High-Engagement Users in December 2021

	Intervention group	
	[400,100]	Control
Female	0.554	0.465
	(0.497)	(0.502)
Age	35.399	35.651
	(13.160)	(14.310)
Ages 18-27	0.346	0.349
	(0.476)	(0.479)
Ages 28-37	0.289	0.279
	(0.453)	(0.451)
Ages 38+	0.366	0.372
	(0.482)	(0.486)
Employee	0.505	0.605
	(0.500)	(0.492)
Self-employed/owns business	0.343	0.337
	(0.475)	(0.476)
Student	0.099	0.047
	(0.299)	(0.212)
Retired	0.026	0.000
	(0.159)	(0.000)
Unemployed/other	0.026	0.012
	(0.159)	(0.108)
Observations	7,587	86

Notes: This table shows descriptives for new users that were referred by high-engagement users that participated in interventions in December 2021. High-engagement customers are those that were eligible because they had at least one purchase in the last 60 days. Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A14:
Descriptives of New Users: Referred by Low-Engagement Users in September 2021

	Intervention group		
	[100,0]	[300,0]	Control
Female	0.573	0.540	0.574
	(0.495)	(0.499)	(0.497)
Age	35.063	35.237	32.722
	(12.027)	(11.604)	(11.055)
Ages 18-27	0.313	0.306	0.383
	(0.464)	(0.461)	(0.488)
Ages 28-37	0.344	0.318	0.330
	(0.475)	(0.466)	(0.472)
Ages 38+	0.343	0.376	0.287
	(0.475)	(0.485)	(0.454)
Employee	0.488	0.504	0.600
	(0.500)	(0.500)	(0.492)
Self-employed/owns business	0.385	0.369	0.270
	(0.487)	(0.483)	(0.446)
Student	0.087	0.093	0.096
	(0.283)	(0.291)	(0.295)
Retired	0.015	0.017	0.026
	(0.120)	(0.129)	(0.160)
Unemployed/other	0.025	0.017	0.009
	(0.156)	(0.129)	(0.093)
Observations	686	708	115

Notes: This table shows descriptives for new users that were referred by low-engagement users that participated in interventions in September 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A15:
Descriptives of New Users: Referred by Low-Engagement Users in October 2021

	Intervention group		
	[100,0]	[100,100]	Control
Female	0.576	0.564	0.578
	(0.494)	(0.496)	(0.496)
Age	35.114	34.778	35.667
	(12.035)	(11.434)	(12.435)
Ages 18-27	0.321	0.321	0.299
	(0.467)	(0.467)	(0.460)
Ages 28-37	0.318	0.324	0.327
	(0.466)	(0.468)	(0.471)
Ages 38+	0.362	0.355	0.374
	(0.481)	(0.479)	(0.486)
Employee	0.513	0.502	0.381
	(0.500)	(0.500)	(0.487)
Self-employed/owns business	0.370	0.353	0.476
	(0.483)	(0.478)	(0.501)
Student	0.089	0.097	0.075
	(0.285)	(0.297)	(0.264)
Retired	0.013	0.010	0.027
	(0.115)	(0.098)	(0.163)
Unemployed/other	0.014	0.038	0.041
	(0.119)	(0.192)	(0.199)
Observations	1,048	626	147

Notes: This table shows descriptives for new users that were referred by low-engagement users that participated in interventions in October 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A16:
Descriptives of New Users: Referred by Low-Engagement Users in November 2021

	Intervention group	
	[300,0]	Control
Female	0.557	0.575
	(0.497)	(0.496)
Age	34.615	33.142
	(11.940)	(10.015)
Ages 18-27	0.337	0.339
	(0.473)	(0.475)
Ages 28-37	0.325	0.370
	(0.468)	(0.485)
Ages 38+	0.338	0.291
	(0.473)	(0.456)
Employee	0.522	0.543
	(0.500)	(0.500)
Self-employed/owns business	0.362	0.339
	(0.481)	(0.475)
Student	0.079	0.094
	(0.270)	(0.294)
Retired	0.017	0.008
	(0.130)	(0.089)
Unemployed/other	0.018	0.016
	(0.135)	(0.125)
Observations	1,625	127

Notes: This table shows descriptives for new users that were referred by low-engagement users that participated in interventions in November 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.

Table A17:
Descriptives of New Users: Referred by Low-Engagement Users in December 2021

	Intervention group	
	[300,0]	Control
Female	0.560	0.583
	(0.497)	(0.515)
Age	34.386	37.417
	(12.025)	(9.170)
Ages 18-27	0.343	0.083
	(0.475)	(0.289)
Ages 28-37	0.319	0.500
	(0.466)	(0.522)
Ages 38+	0.338	0.417
	(0.473)	(0.515)
Employee	0.465	0.750
	(0.499)	(0.452)
Self-employed/owns business	0.398	0.167
	(0.490)	(0.389)
Student	0.099	0.083
	(0.299)	(0.289)
Retired	0.013	0.000
	(0.115)	(0.000)
Unemployed/other	0.024	0.000
	(0.152)	(0.000)
Observations	1,188	12

Notes: This table shows descriptives for new users that were referred by low-engagement users that participated in interventions in December 2021. Low-engagement customers are those that were eligible because they had at least one transaction in the last 90 days (and were not eligible as high-engagement customers). Monetary incentives are denoted by $[w, z]$, where w is the amount in MXN that the user making the referral receives and z is the amount in MXN received by the new user that was referred. The control group corresponds to $[0, 0]$. Averages are shown with standard deviations in parentheses.